Efficiency and water use:
Dynamic effects of irrigation technology adoption

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Author Note

This work was supported by a National Science Foundation Research Traineeship (NRT) program funded by NSF under Award No. 1828571 and by the USDA National Institute of Food and Agriculture, Agricultural and Food Research Initiative Competitive Program, Agriculture Economics and Rural Communities, grant # 2017-67023-26276.

Abstract

With the United States preparing to make a historic investment in drought mitigation, clarifying the impact of irrigation efficiency improvements on water resources is critically important. This paper uses two transitions in irrigation technology to investigate whether rebound effects cause such efficiency improvements to increase resource extraction, a phenomenon known as Jevon's paradox. We demonstrate how staggered adoption of an irrigation technology and dynamic treatment effects causes two-way fixed effects (TWFE) to indicate the wrong sign for the effect on withdrawals. Using an estimator appropriate for these circumstances, we find no significant evidence of Jevon's paradox. The dynamic effects we find explain this discrepancy and, perhaps more importantly, reveal irrigators' process of adaptation to each new technology at the intensive and extensive margins.

JEL Codes: Q15, Q25

1 Introduction

As a historic drought stresses the water resources of the western United States, agricultural producers and policy makers alike are under pressure to find solutions which ensure food production with an increasingly scarce resource (Rosa et al. 2018; Droppers et al. 2021). In response to this crisis, the Inflation Reduction Act of 2022 includes four billion dollars to facilitate drought mitigation in states west of the Mississippi and specifies the following as one of three approved activities: “Voluntary system conservation projects that achieve verifiable reductions in use of or demand for water supplies or provide environmental benefits in the Lower Basin or Upper Basin of the Colorado River” (117th Congress 2022). Public reporting concerning this allocation, despite the unspecified means of achieving reductions in the previous statement, suggested producers in priority basins could be paid to install more efficient irrigation technologies (J. Wilson 2022). While improving irrigation efficiency sounds congruent with the goal of continuing production with scarcer resources, the literature suggests adoption of increasingly efficient irrigation technologies may be counterproductive and result in the degradation of water resources.

One reason for adverse consequences of technology adoption is based on the hydrologic water balance in a system. While the technology can affect water withdrawals, it may also affect return flows, which highlights the important distinction between water use and consumption (Ward and Pulido-Velazquez 2008; Huffaker 2008). The second reason for adverse consequences of technology adoption is the potential for Jevon’s paradox, where changes in behavior following technology adoption could cause an increase in water use. Rebound effects are generated when resource users adapt to improvements in resource use efficiency such that the resource savings produced by the increase in efficiency are partially or completely offset

(Greening, Greene, and Difigli 2000). Jevons' paradox occurs if the rebound effect is large enough to create a net increase in resource consumption following an efficiency improvement (Jevons 1865; Alcott 2005). While the water balance effect is a critical component of water management—especially in surface water contexts—we focus our analysis on the potential for rebound effects and Jevon's paradox in water withdrawals.

In this paper, we estimate the effect of two efficiency-improving transitions in irrigation technology on Kansas irrigators' groundwater withdrawals using a Difference-in-Differences identification strategy and an estimation approach amenable to settings with staggered adoption and heterogeneous treatment effects. We find irrigators who switched from flood to center pivot irrigation avoided reducing irrigated acreage by decreasing withdrawals immediately after changing technologies.[1] Therefore, the higher efficiency of the new technology extended the productive life of the aquifer. For the conversion from traditional center pivot to LEPA irrigation, we find minimal impacts on withdrawals in the short run and steadily larger decreases over several years. In summary, there is no significant evidence of Jevon's paradox in groundwater withdrawals. But, for both technology transitions, the magnitudes of reductions in withdrawals suggest ex-ante engineering estimates of water savings from the efficiency improvements are overly optimistic.

Our paper makes three primary contributions. First, we estimate the effect of an efficiency improvement on the behavior of profit-maximizing producers. Much of the literature on rebound effects examines consumer behavior in response to changes in energy efficiency (Chan and Gillingham 2015; Borenstein 2015). The first wave of empirical research found rebound effects due to improvements in energy efficiency offset a small fraction of potential

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[1] Descriptions of the design and engineering efficiencies for the irrigation systems in our analysis are provided in the subsequent section.

savings but rarely caused Jevon's paradox (Sorrell, Dimitropoulos, and Sommerville 2009; Gillingham et al. 2013). A more recent strand of empirical work emphasizes the role of technological heterogeneities and biased efficiency estimates (Burlig et al. 2020; Fowlie, Greenstone, and Wolfram 2018; Christensen et al. 2023). Alpizar, Carpio, and Ferraro (2023) use a randomized control trial to estimate the dynamic treatment effects of households receiving water-efficient technologies. But there are few papers with convincing causal estimates of the impacts of efficiency improvements on producer behavior—with exceptions on water use efficiency noted below. In general, our results support the conclusions in the consumer contexts—savings are half of engineering estimates at best, but do not support Jevon's paradox.

Our second contribution is to show the importance of estimating dynamic treatment effects in a setting with staggered adoption of efficiency-improving technologies (Goodman-Bacon 2021). As we demonstrate in a simulation context, if the effect of adopting the efficiency-improving technology grows stronger over time such that contemporaneous reductions in groundwater use by later adopters are smaller than those of early adopters, faulty comparisons of these groups by two-way fixed effects (TWFE) estimation can create the illusion of later adopters increasing water use. In comparison to our preferred estimation approach which accommodates staggered adoption and dynamic treatment effects, we find using TWFE produces average treatment effects of the opposite sign and dynamic treatment effects exhibiting the opposite trend over time. Beyond irrigation technologies, we anticipate that future studies of technology adoption will benefit from our work given that staggered adoption is typical of technology diffusion processes (Griliches 1957; 1958; Feder, Just, and Zilberman 1985; Sunding and Zilberman 2001).

Our estimates clarify the effect of efficiency improvements on withdrawals in contexts where return flows are non-recoverable. Withdrawals decreased in over 75% of the studies on increases in irrigation efficiency reviewed by Berbel et al. (2015) and Pérez-Blanco, Hrast-Essenfelder, and Perry (2020), and both reviews find efficiency improvements were most likely to conserve water in areas with limited return flows. Two influential studies in Kansas stand out as exceptions to this conclusion. Pfeiffer and Lin (2014) find that the adoption of Low Energy Precision Application (LEPA) irrigation, a more efficient center pivot system described further in the next section, increased withdrawals in comparison to a traditional center pivot system. Li and Zhao (2018) also find significant increases in withdrawals due to LEPA adoption, but the magnitude of the effect depends on the size of irrigators' water rights. In contrast to these previous studies, we find that LEPA adoption led to a small and statistically insignificant decrease in water withdrawals.

As a third contribution, our results for the effect of conversions from flood (a gravity-fed system) to center pivot (a pressurized system) irrigation constitute a timely contribution to the literature on irrigation and agricultural water use since most econometric studies focus on other technology transitions. In much of the United States, India, and South and Southeast Asia, there is a widespread and ongoing transition from gravity-fed to pressurized systems (Hrozencik and Aillery 2022; Siebert et al. 2010). Kansas irrigators were early adopters of pressurized systems, so the two decades of dynamic treatment effects we estimate provide valuable insights for regions currently undergoing or anticipating a similar transition. In 2018 for example, just 3 percent of the 2.4 million irrigated acres in Kansas used a gravity-fed system, but in the same year 45 percent of the 2.5 million irrigated acres in the neighboring state of Colorado used a gravity-fed system (United States Department of Agriculture 2019). Our results show that irrigators who made this conversion avoided reducing irrigated acreage, thus avoiding the primary source of economic losses due to aquifer depletion (Perez-Quesada, Hendricks, and Steward 2023).

2 Background on Kansas water rights and irrigation technologies

In Kansas, groundwater is the source of roughly 92% of irrigation water due to the importance of the High Plains Aquifer in western Kansas (Kenny and Hansen 2004). In order to irrigate, a farmer must obtain a water right permit that specifies the total quantity that may be pumped annually, the maximum rate at which the water can be extracted, and the location where the water may be used (i.e., the place of use). The water right is also given a priority number, since Kansas follows the prior appropriation doctrine. The quantity of water allocated to a water right is determined by the amount of water pumped during a perfection period as long as it was deemed reasonable and beneficial use (Peck et al. 1988). To be authorized, a water right also needs to not impair the ability of neighboring senior water rights to exercise their right.[2] Water rights in Kansas developed rapidly between 1950 and 1980 (Sampson and Perry 2019). Development of water rights slowed dramatically after 1980 due to the introduction of Groundwater Management Districts that implemented well-spacing requirements and closed areas to further water right development (Edwards 2016). While it became difficult to acquire new water rights after 1980, existing irrigators could adjust the area irrigated within the maximum area of the authorized place of use.

The first change in irrigation technology that we study is the transition from using gravity-driven systems, referred to as flood or furrow irrigation, to a pressurized system involving a center

[2] See https://agriculture.ks.gov/divisions-programs/dwr/water-appropriation/new-applications-and-permits.

pivot. In Kansas, furrow irrigation is the most common type of gravity-fed irrigation and groundwater is typically transported from the well to the uphill end of furrows in pipe or tubing rather than open channels (United States Department of Agriculture 2019). As such, the principal water losses for furrow irrigation systems in our context would be caused by runoff, evaporation as water travels within furrows, or deep-percolation. Center pivot systems pump pressurized water through a series of sprinkler heads, or nozzles, arranged along a rotating length of pipe suspended above the crops. In addition to run-off and deep percolation, center pivot systems are also subject to water losses due to drift, when wind carries the water away from its intended target, and evaporation occurring in the air or canopy (Rogers, Alam, and Shaw 2008).

Despite these additional sources of loss, there are two advantages of pressurized center pivot systems worth emphasizing in our research context. First, the potential application efficiency—the fraction of applied water which is stored in the root zone—for a typical center pivot irrigation system is between 75% and 85% and for a furrow irrigation system it ranges from 45% to 65% (Irmak et al. 2011). Second, as they do not rely on gravity to convey water, center pivot systems can irrigate areas where the topography would make gravity-fed irrigation impossible or prohibitively expensive (NRCS 1997). On the other hand, center pivot systems typically irrigate a circular area that could be smaller than a rectangular area irrigated by a furrow system. Therefore, the change in area from a conversion is ambiguous.

The second transition in irrigation technology, adoption of LEPA devices, involves modifications to center pivot irrigation systems which improve the application efficiency of the system and reduce the necessary operating pressure. The nozzles in a LEPA system hang below the main pipe of the center pivot system, or even within the crop canopy, and thereby reduce evaporative losses by dispensing water closer to the root zone. As a result, installing LEPA devices can increase the potential application efficiency of a center pivot system to be between 80% and 90% (Irmak et al. 2011). In addition, as highlighted in Pfeiffer and Lin (2014), the operating pressure required for LEPA devices is as little as one eighth that of other center pivot sprinkler configurations (Rogers, Alam, and Shaw 2008). As such, the marginal cost of applying a unit of groundwater decreases due to a reduction in fuel costs.

While each of the irrigation system conversions that we study result in an increase in application efficiency, it is important to recognize that there are other factors that could also affect water use. Each conversion leads to a decrease in the cost of applying water and the configuration of the system affects the area irrigated. Technology conversions in different contexts that affect efficiency (e.g., appliances and transportation) also likely affect behavior in ways other than efficiency that are important to recognize.

3 Data

3.1 WIMAS

Historical water use data are obtained from the Water Information Management and Analysis System (WIMAS), a joint effort by the Kansas Department of Agriculture, Division of Water Resources and Kansas Geological Survey (Wilson et al. 2005). Water right records within WIMAS contain annual reported water withdrawals, irrigated acreage, the point of diversion where water is withdrawn, the crop grown, and the irrigation technology, along with other data. The outcome variable we use to measure irrigation intensity, depth applied (i.e., total withdrawals per acre), is constructed by dividing total withdrawals by acres irrigated.

Within WIMAS, multiple water rights can be associated with a single well, or vice versa, so we aggregate water use to a unit of observation called the water right group (Rosenberg 2020). Specifically, we begin by matching water rights and their associated points of diversion to their place of use—the specific tract where the water right is authorized to be applied. Then, we find overlaps between places of use based on shared points of diversion or shared water rights to define the water right groups. As such, water right groups are networks of water rights sharing common points of diversion or places of use.[3] Using water right groups as the unit of aggregation avoids the concern of water use being shuffled between multiple water rights within the same place of use and thus allows us to accurately track changes in water withdrawals through time, even if the related water rights or points of diversion change for administrative reasons.

As WIMAS is comprised of data reported by individual irrigators, there are oddities and extreme values within some records. To prevent these values from distorting our results, we remove observations that have total withdrawals, acres irrigated, or depth applied greater than the 99th percentile after performing the aggregation to the water right group level. Additionally, we remove observations with a reported quantity for withdrawals but zero reported irrigated acres or vice versa. Most of the time irrigation technology is not reported when withdrawals or acres irrigated are equal to zero. There are a few times when the irrigation technology is reported but, in these cases, we replace the technology as missing to be consistent. The number of water right groups and observations removed by each of these subsequent filters is detailed in Appendix A. Summary statistics for the final dataset are presented in table 1. Figure 1 illustrates the variation of the three dependent variables and the adoption of irrigation technologies over time. We use "traditional center pivot" to refer to a center pivot system without LEPA.

Table 1: Summary statistics for water right groups with flood, traditional center pivot, or LEPA irrigation systems across all years from 1991 to 2019.

[3] Within WIMAS, records are uniquely identified by a combination of the water use year, water right details, and well information called a "wuadet_key." In the dataset containing all three irrigation technologies, 67% of the water right groups have a single "wuadet_key" value in all years. Another 19% of water right groups have two or fewer "wuadet_key" values in all years, 7% have 3 or fewer in any year, and the remaining 7% have 4 or more.

Variable	N	Mean	Median	Std. Dev.	Min.	Max.
Total withdrawals (AF)	181,052	208.06	156.67	190.18	0.01	1,431.00
Flood irrigation	34,476	178.69	107.90	204.86	0.01	1,426.96
Traditional center pivot	36,232	201.60	155.58	181.04	0.02	1,427.24
LEPA irrigation	110,344	219.36	166.00	187.25	0.01	1,431.00
Irrigated acres	181,052	185.01	130.00	138.02	1.00	910.00
Flood irrigation	34,476	152.98	111.00	142.90	1.00	910.00
Traditional center pivot	36,232	179.42	130.00	123.76	4.00	910.00
LEPA irrigation	110,344	196.85	130.00	139.20	1.00	910.00
Depth applied (ft)	181,052	1.11	1.10	0.49	0.00	2.47
Flood irrigation	34,476	1.12	1.08	0.56	0.00	2.47
Traditional center pivot	36,232	1.10	1.09	0.49	0.00	2.47
LEPA irrigation	110,344	1.11	1.10	0.46	0.00	2.47
Soil variables						
Sand content (%)	181,052	36.17	19.68	28.13	5.23	97.35
Silt content (%)	181,052	41.63	51.66	21.46	0.60	71.11
Available water capacity (cm/cm)	181,052	0.17	0.18	0.04	0.05	0.22
Pre-development aquifer variables						
Specific yield	181,052	16.75	17.00	3.86	0.00	25.00
Depth to water	181,052	65.43	53.99	56.12	0.00	260.19
Saturated thickness	181,052	153.64	130.99	113.92	-0.16	610.69
Hydraulic conductivity	181,052	82.09	97.00	26.03	0.00	135.00
Weather variables						
Preseason precipitation (in.)	181,052	4.79	4.30	2.46	0.33	15.20
Growing season precipitation (in.)	181,052	15.37	14.73	5.18	2.62	38.67
Preseason evapotranspiration (in.)	181,052	10.72	10.73	1.06	7.21	13.85
Growing season evapotranspiration (in.)	181,052	31.00	30.98	1.86	26.16	37.22

Note: “Preseason” includes the months from January to April, and “growing season” contains from May to September.

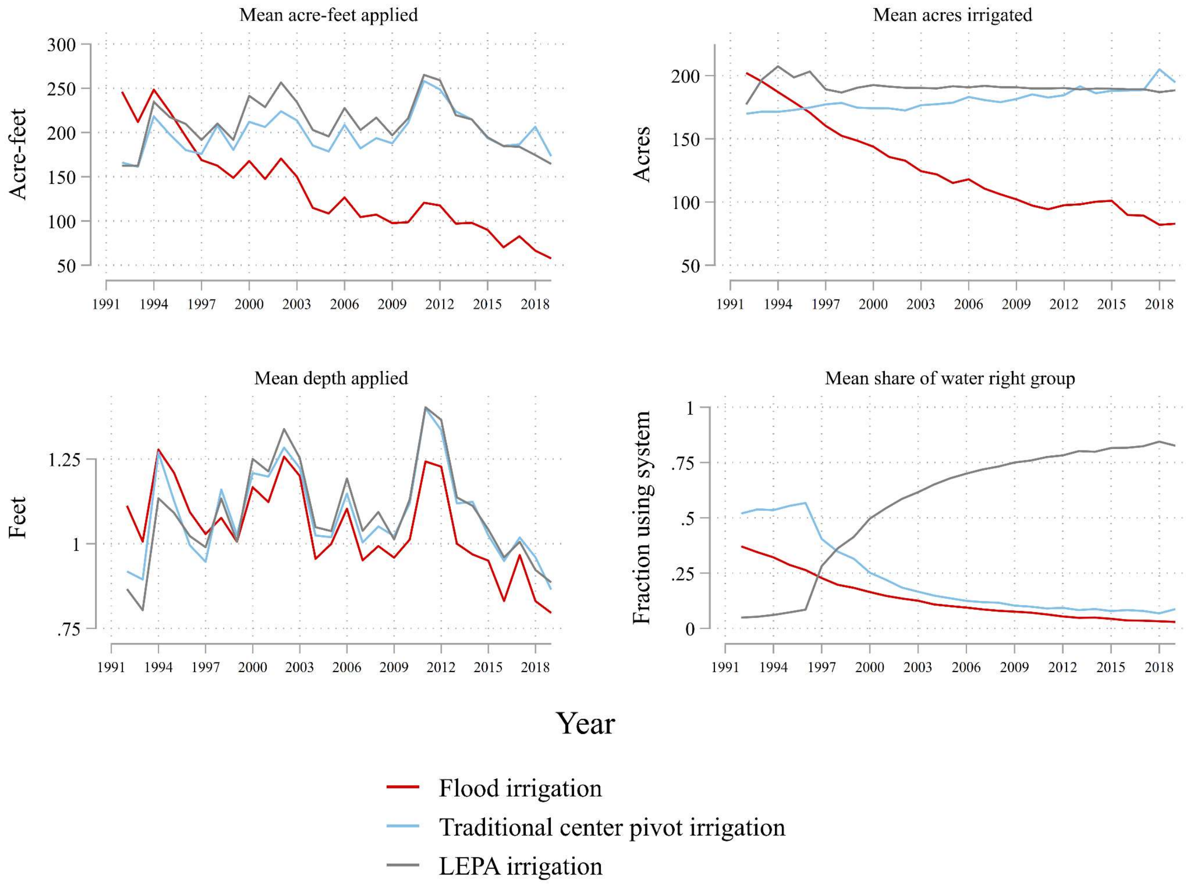

Figure 1: Average total withdrawals, acres irrigated, depth applied, and mean share of water right groups by irrigation system over time.

3.2 Soil, weather, and aquifer characteristics

Monthly data for cumulative precipitation, average maximum temperature, and average minimum temperature are from the Parameter-elevation Regressions on Independent Slopes Model repository maintained by Oregon State University (PRISM Climate Group 2014). We calculate the mean value of each variable for every Public Land Survey System (PLSS) section (roughly 1 square mile) in Kansas and match to water right groups by place of use. Reference evapotranspiration data are generated with water right group specific data on average temperature, latitude, and elevation using the Penman-Monteith equation as outlined in Allen, Pereira, and Smith (1998).[4] For the precipitation and evapotranspiration covariates, we aggregate the values into "preseason" (January-April) and "growing season" (May-September) variables.

The elevation data used in the Penman-Monteith equation are from the Soil Survey Geographic (SSURGO) Database along with other time invariant soil characteristics including the water holding capacity, soil texture, and hydraulic class (Soil Survey Staff 2022). Soil characteristics reflect the dominant soil type at the section level and are matched to water right groups' respective places of use. Finally, time invariant hydrologic characteristics of the High Plains Aquifer at the section level are obtained from the Kansas Geological Survey and include the predevelopment saturated thickness, predevelopment depth to groundwater, specific yield, and hydraulic conductivity. Summary statistics for both the time varying and invariant covariates are displayed in the bottom section of Table 1.

3.3 Creation of technology adoption sub-samples

To isolate the effect of each respective technology adoption, we create two sub-samples of our panel dataset. The first contains irrigators who use flood, traditional center pivot, or LEPA irrigation and allows us to isolate the effect of transitioning from flood irrigation to a center pivot system. For the second, we only include irrigators using traditional center pivot or LEPA irrigation, so we can estimate the effect of adopting LEPA.

The difference-in-differences identification strategy and estimation approach we employ, detailed in the next section, requires modifications to these sub-samples to ensure we construct

[4] We construct reference evapotranspiration data using temperature data from PRISM, as opposed to using remote-sensed or local measured values, to avoid introducing the endogenous relationship between water use and evapotranspiration. So long as the temperature data from PRISM are unaffected by irrigation behavior, our measure of reference evapotranspiration is independent of irrigation behavior. In contrast, actual evapotranspiration depends on the crop and the amount of water applied.

appropriate counterfactual outcomes using the behavior of irrigators who do not adopt the new technology. For both sub-samples, we remove water right groups that have already adopted the more efficient technology before the first year of the sub-sample to preclude the use of faulty controls. For the same reason, we do not include water right groups who changed technologies during the sub-sample time period if we do not observe the change occurring between consecutive years due to missing data. In these instances, we are unable to determine when the transition occurred.

As our empirical approach requires discrete treatment categories, we remove any water right groups using multiple technologies in a single year. Finally, we remove water right groups that report adopting the new technology but then revert to the older technology at a later point in time.[5] Most of the transitions from flood to center pivot occurred in the 1990s and early 2000s (figure A.1). Conversions from flood to traditional center pivot systems devices are concentrated between 1992 and 1997, while conversions from flood to LEPA irrigation are more uniformly distributed throughout the time series with larger adoption cohorts between 1997 and 2002 (figure A.2). Conversions from traditional center pivot to LEPA are largest between 1997 and 2005 (figure A.1).

To estimate the effect of transitioning from flood to center pivot irrigation, we exclude groups that never adopt center pivot irrigation by 2019. As shown in figure 2, there are few irrigators remaining that use flood irrigation. As such, these irrigators who remain using flood irrigation may be systematically different from those that previously adopted center pivot

[5] For example, some groups report switching back to flood irrigation after converting to center pivot. Converting a technology involves large, fixed costs so it is highly unlikely that a farmer would revert back to an older technology. There are a couple of reasons why reverting might get reported. One reason is that it could be a reporting error. A second reason is that different portions of the water right group that have different technologies could have been irrigated in different years. For example, field A has flood technology and field B has center pivot but both fields are in the same water right group. If the farmer alternates between irrigating field A and B in different years, then it will give the false appearance of technology conversion.

irrigation, violating the conditions necessary for our identification strategy. In addition, we are unable to estimate the impact of adopting center pivot irrigation for water right groups who adopt from 2016 onward using our preferred estimator due to computational limitations with small cohorts.[6] As such, we remove the years from 2016 onward for the flood to center pivot transition (Table 2). The final unbalanced panel dataset contains 1,628 water right groups in total, 29% of the water right groups are observed every year and 90% have at least 15 years of data.

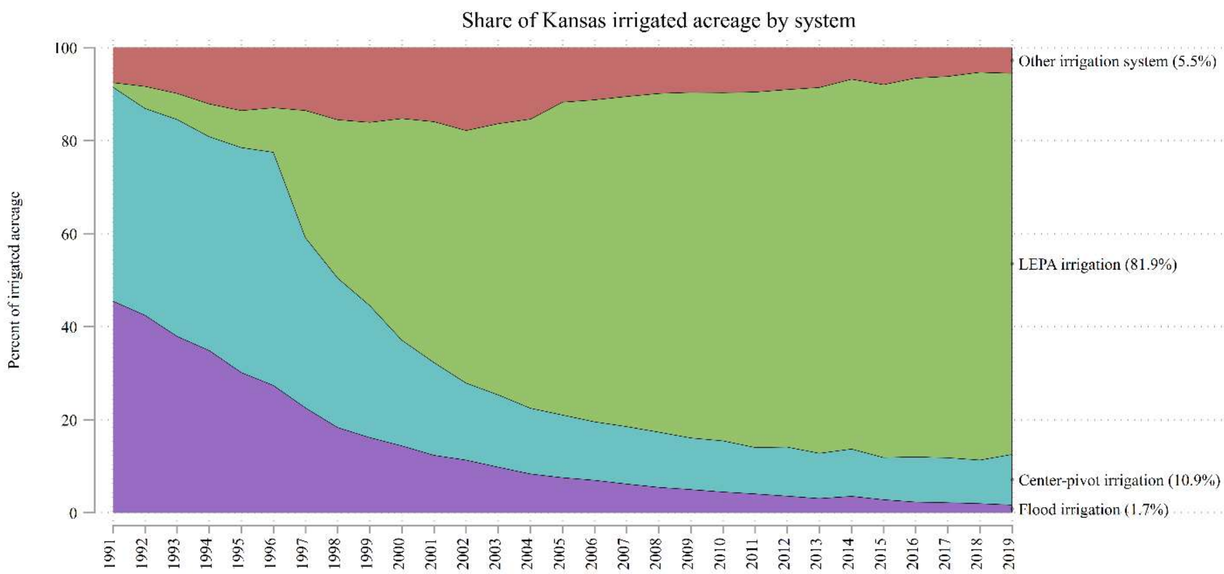

Figure 2: Percent of Kansas' total irrigated acreage using irrigation technologies over time.

For the conversion from traditional center pivot to LEPA sub-sample, we use the entire sample period 1991-2019 and include water right groups that never adopted LEPA since about 11% of acres are still irrigated by traditional center pivots in 2019. The final unbalanced panel for the LEPA adoption sub-sample contains 3,989 water right groups (table 2). Of the water right

[6] The R package we use is limited in its estimation of treatment effects for small cohort sizes, and the 2016 to 2019 cohorts contain only 32 water right groups in total (Callaway and Sant'Anna 2021).

groups in the LEPA adoption sub-sample, 42% are observed in all 29 years and 90% have at least 15 years of data. The percent of irrigators in each treatment group for both sub-samples is depicted in figure A.3.

Table 2: Sub-sample characteristics for water right groups in each technology transition.

Variable	Technology transition panel datasets	
	Flood adopting traditional center pivot or LEPA	Traditional center pivot adopting LEPA
Years included	1991-2015	1991-2019
Water right groups adopting within sub-sample years	1,596	3,716
Water right groups adopting after sub-sample years	32	N/A
Never-adopter water right groups	Excluded	273

4 Empirical analysis

We use a Difference-in-Differences (DID) approach to identify the effect of the two technology transitions on irrigators' groundwater use. In essence, the DID approach compares the evolution in irrigation behavior over time of water right groups who adopt the new technology, the treated, to those who do not, the controls. The parallel trends assumption for this approach requires that the change in groundwater use for adopting and non-adopting water right groups must evolve identically over time in the counterfactual scenario wherein no one adopts the new technology.

The conventional approach to this type of analysis was to estimate a two-way fixed effects (TWFE) model with time-varying covariates. However, the staggered nature of irrigation technology adoption and the possibility of heterogeneous treatment effects in our empirical setting suggest TWFE could be biased. As demonstrated by Goodman-Bacon (2021), TWFE estimation generates a weighted average of simpler two-by-two difference-in-differences (DD) estimators including two potentially erroneous comparisons between early and later adopters. For example, consider the case where adoption of an irrigation technology decreases groundwater use, and the treatment effect becomes more negative over time. In this case, when late adopters first adopt, they decrease water use less than early adopters. This causes TWFE to be biased upward since TWFE uses early adopters as a faulty control comparison for late adopters. We depict an illustrative scenario with a Monte Carlo simulation in appendix B where TWFE suggests adoption of a technology causes Jevon's paradox, despite the exact opposite being true.[7]

To avoid improper comparisons of late and early adopters, we employ the estimation strategy described in Callaway and Sant'Anna (2020). An additional advantage of the Callaway and Sant'Anna's (2020) approach is the use of a doubly robust estimator, indicated by the subscript dr in subsequent equations, meaning the treatment effect is recovered if either the treatment effect evolution or the propensity score models are properly specified (Sant'Anna and Zhao 2020). We use the superscript ny to indicate we use the specifications in Callaway and Sant'Anna (2020) that include "not-yet-treated" observations, pre-adoption data in our context, as controls. As mentioned in Section 3, we exclude the "never-treated" water right groups for the transition from flood to center pivot irrigation, but we include the "never-treated" units for the conversion from traditional center pivot to LEPA irrigation.

[7] While previous studies have described the bias of two-way fixed effects in detail (Borusyak 2018; de Chaisemartin and D'Haultfoeuille 2020; Sun and Abraham 2021; Goodman-Bacon 2021), our purpose in providing this example is to illustrate the bias in the context of irrigation technology adoption and water use with plausible parameter values.

To explain our estimation approach, we begin by introducing some notation. Let $Y_{i,g,t}$ denote the outcome of interest (i.e., withdrawals, acres irrigated, or depth applied) for water right group i in adoption cohort g in year t, $D_{i,g,t}$ is the binary variable indicating if unit i in cohort g has adopted the new technology at time t, and $Z_{i,g}$ denotes time-invariant soil and aquifer characteristics. Cohorts are comprised of all water right groups who first adopt the new irrigation technology in year g. The approach in Callaway and Sant'Anna (2020) produces unbiased estimates of the average treatment effect on the treated (ATT) by estimating and aggregating group-time average treatment effects. In our context, each group-time average treatment effect, $ATT(g,t)$, represents the average effect of adopting the more efficient irrigation technology at time t for the cohort of individuals who first adopted the technology in year g.

Constructing the $ATT_{dr}^{ny}(g,t)$ estimator is a two-step process beginning with estimating the population outcome regression, $m_{i,g,t}^{ny}(Z_{i,g})$, and the propensity score, $p_{i,g,t}(Z_{i,g})$. Letting N indicate the total sample size and defining $G_{i,g}$ as an indicator variable equal to one if irrigator i is first treated in period g, the parametric estimators of the outcome regression and propensity score functions, $\widehat{m}_{i,g,t}^{ny}(Z_{i,g};\hat{\beta}_{i,g,t}^{ny})$ and $\hat{p}_{i,g,t}\left(Z_{i,g};\hat{\pi}_{i,g,t}\right)$

$$\widehat{ATT}_{dr}^{ny}(g,t)=\frac{1}{N}\sum\nolimits_{\forall i}\left[\left(\widehat{w}_g^{treat}-\widehat{w}_g^{comp,ny}\right)\left(Y_{i,g,t}-Y_{i,g,g-1}-\widehat{m}_{g,t}^{ny}\left(Z_{i,g};\hat{\beta}_{g,t}^{ny}\right)\right)\right] \qquad (1)$$

where

$$\widehat{w}_g^{treat}=\frac{G_{i,g}}{\frac{1}{N}\sum_{\forall i}\left(G_{i,g}\right)};\ \widehat{w}_g^{comp,ny}=\frac{\frac{\hat{p}_{i,g,t}\left(Z_{i,g};\hat{\pi}_{i,g,t}\right)\left(1-D_{i,g,t}\right)\left(1-G_{i,g}\right)}{1-\hat{p}_{i,g,t}\left(Z_{i,g};\hat{\pi}_{i,g,t}\right)}}{\frac{1}{N}\sum_{\forall i}\left(\frac{\hat{p}_{i,g,t}\left(Z_{i,g};\hat{\pi}_{i,g,t}\right)\left(1-D_{i,g,t}\right)\left(1-G_{i,g}\right)}{1-\hat{p}_{i,g,t}\left(Z_{i,g};\hat{\pi}_{i,g,t}\right)}\right)}.$$

In equation 1, the doubly robust specification of Callaway and Sant'Anna's (2020) estimator displays two methods of addressing covariate-driven non-parallel trends. The first method, subtracting $\widehat{w}_g^{comp,ny}$ from the population weight, demonstrates the inverse probability weighting approach to DID settings which compares the outcomes of treatment and control groups using the probability of treatment conditional on covariates (Abadie 2005). The second method, subtracting $\widehat{m}^{ny}_{i,g,t}(Z_{i,g}; \hat{\beta}^{ny}_{i,g,t})$ from the outcome evolution, uses the outcome evolution for control group observations with matching time-invariant covariates to address differential trends in the outcomes (Heckman, Ichimura, and Todd 1997).

For our estimations, we use the default option for Callaway and Sant'Anna's (2021) *did* R package which employs the inverse probability tilting estimator of Graham, Campos De Xavier Pinto, and Egel (2012) to estimate propensity scores and weighted-least squares to estimate the outcome regressions. To account for multiple hypothesis testing, we use the simultaneous inference procedure described in Callaway and Sant'Anna (2020). Specifically, we use cluster bootstrap standard errors with 1,000 iterations to generate simultaneous confidence bands at the $\alpha = 0.05$ level. The covariates we include in $Z_{i,g}$ are the pre-development saturated thickness and hydraulic conductivity of the aquifer, the available water capacity and soil texture, and the pre-treatment acre-feet the water right group applied in the first year they appear in each sub-sample dataset.

Once estimated, the individual $\widehat{ATT}^{ny}_{dr}(g,t)$ estimates must be aggregated to generate an estimate of the average treatment effect, $\hat{\delta}^{CS}$. For a given value of g, we first create the following average treatment effect for each cohort, $\hat{\delta}^{CS}(g)$, by averaging the treatment effects across all values of $t \geq g$ and dividing by the maximum number of periods an irrigator in group g could be treated for:

$$\hat{\delta}^{CS}(g) = \frac{1}{T-g+1} \sum_{t=g} \widehat{ATT}^{ny}_{dr}(g,t). \qquad (2)$$

Then, we take a weighted average of the $\hat{\delta}^{CS}(g)$ values across all cohorts to produce the final estimate of the ATT. Letting N_g indicate the number of observations across all irrigators in cohort g, the weights for this final aggregation are the probabilities of belonging to a given cohort conditional on being in a treated cohort,

$$\hat{\delta}^{CS} = \frac{1}{\sum_{g=1}^{T} N_g} \sum_g N_g * \hat{\delta}^{CS}(g). \tag{3}$$

We employ one other aggregation so we can plot event-study style estimates of dynamic treatment effects. In the following equation, we let l be the number of years since an irrigator adopted the new technology. Additionally, we use $N_{g,l}$ to indicate the number of irrigators in cohort g who are observed for l periods after the new technology is adopted. The following equation for $\hat{\delta}^{CS}(l)$ estimates the effect of l years using the new technology:

$$\hat{\delta}^{CS}(l) = \frac{1}{\sum_{g=1}^{T-l} N_{g,l}} \sum_{g \in G} N_{g,l} * \widehat{ATT}_{dr}^{ny}(g, g+l). \tag{4}$$

There are five necessary assumptions for the individual $\widehat{ATT}_{dr}^{ny}(g,t)$ estimates and the aggregations to identify their respective effects. The first two assumptions concern the design of the pseudo experiment, imposing restrictions on the treatment variable and sampling process. First, treatment must be irreversible, meaning no irrigator can adopt the new technology and then switch back to the earlier technology in a later time period. We are confident this assumption holds for our sample because the technology transitions involve substantial costs and—as mentioned in Section 3.3—we removed water right groups that reported reverting back to the prior technology. Second, the panel dataset must be representative of the overall population. As the WIMAS dataset we employ is comprised of records that all irrigators in Kansas are required to provide on their annual groundwater use, and flow meters were required for all wells beginning in 2000, we are also confident this second assumption holds (Kansas Statutes Annotated 1988; Kansas Administrative Regulations 2000).

The next three assumptions, the identifying assumptions, are concerned with establishing conditional parallel trends between adopters and never adopters. The third assumption requires the temporal extent of behavior in anticipation of adopting the new technology to be pre-specified. We assume there is no anticipation behavior in our context because groundwater rights in Kansas ascribe irrigators an annual quantity of water which is unaffected by their use in prior years, so there is no strategic reason to adjust water use before adoption. The fourth assumption requires the expected counterfactual outcome evolution for adopters to equal the expected outcome evolution of irrigators who have not yet adopted by the end of the period in question, where both outcome evolutions are conditioned on pre-treatment covariates. Finally, the "overlap" assumption is required to take advantage of the doubly robust version of Callaway and Sant'Anna's (2020) estimator and is commonly employed in the difference-in-differences literature (Sant'Anna and Zhao 2020). In essence, the overlap assumption requires there to be adopters and not-yet or never adopters with similar propensity scores so that the control group's outcome evolution is truly reflective of the adopters' counterfactual outcome. As outlined above, the $\hat{\delta}^{CS}$ estimator matches water right groups based on pre-treatment covariates, and then uses these matched controls to generate counterfactual outcomes.

To provide evidence that these three identifying assumptions hold, we perform the pre-test from Callaway and Sant'Anna (2020) to determine whether the estimated effects of adoption in pre-adoption years are jointly significantly different from zero. While this pre-test does not ensure conditional parallel trends holds with certainty during the treatment period (Roth 2022), it does provide an indication of whether treated and control water right groups behaved similarly prior to adoption. We perform the test for multiple intervals within each sub-sample due to the increased likelihood of failing the pre-test due to random chance when a greater number of pre-treatment periods are added even if the conditional parallel trends assumption is satisfied (Roth 2022). The pre-test results for the flood to center pivot and traditional center pivot to LEPA transitions are displayed in tables D.1 and D.2 within Appendix D. For both transitions, the pre-test passes for all three dependent variables for the period running from 1996 through 2005. In addition, the pre-test passes in most of the five-year windows spanning these two transition's full time series. The exceptions to this statement are the earliest periods from 1991 to 1996.

5 Results and Discussion

First, we show the average treatment effects for each technology change on total withdrawals. We also decompose the effect on total withdrawals into the effect on acres irrigated (i.e., extensive margin) and depth applied (i.e., intensive margin). Then, we present the dynamic treatment effects and discuss the adaptations in irrigation behavior they represent. Next, we include a series of checks to illustrate the robustness of our results. Finally, we show how the dynamic treatment effects we find create biased TWFE estimates and compare our results to those from prior studies of the effect of LEPA adoption. Note, for all inferences presented in the results section, we cluster at the water right group level to address issues of heteroskedasticity and autocorrelation between years.

5.1 Average treatment on the treated estimates

The overall average treatment effect estimates for each transition are plotted in figure 3 as a percent change relative to the mean values of the dependent variables in the pertinent sub-sample. Note that the impact on total withdrawals does not equal the product of the impact on acres irrigated and depth applied because depth-applied values cannot be generated when there are zero irrigated acres reported. Figure 3 shows both the preferred $\hat{\delta}^{CS}$ and biased $\hat{\beta}^{TWFE}$

estimates to visually compare the results.[8] In this sub-section, we focus on the $\hat{\delta}^{CS}$ estimates from our empirical strategy in the previous section. We discuss the $\hat{\beta}^{TWFE}$ estimates in a later sub-section. Additional tables of results are provided in Appendix C.[9]

The estimated effects of changing from flood to center pivot irrigation on acre-feet withdrawn, irrigated acres, and depth applied are displayed in the top row of panels in figure 3. The preferred $\hat{\delta}^{CS}$ estimates for withdrawals and acres irrigated are statistically insignificant increases of 1.5% (2.8 acre-feet) and 6.2% (9.1 acres), respectively. However, this result should not be interpreted as an expansion of irrigated acres, but rather avoiding the loss in irrigated acres that would have occurred with flood irrigation (see figure A.4).[10] There are two main reasons that irrigated acres would have decreased if remaining in the flood system (O'Brian et al. 2000; Peterson and Ding 2005). First, aquifer levels were declining in the region resulting in a slower rate of water extraction at a higher marginal cost. The slower rate of extraction decreases crop yields, especially for inefficient irrigation systems. Second, flood is a labor-intensive technology and labor costs were rising. Our results indicate that water right groups were able to maintain greater irrigated acreage after adopting center pivot irrigation by reducing the depth applied at the intensive margin. We find a statistically insignificant 5.0% decrease in depth-applied due to irrigators switching from flood to center pivot. Note, however, engineering

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[8] We estimate a regression specified as $Y_{i,g,t} = \lambda_{i,g} + \gamma_t + \Phi X_{i,g,t} + \beta^{TWFE} D_{i,g,t} + u_{i,g,t}$, where $\lambda_{i,g}$ and γ_t are fixed effects for water right groups and years respectively, and $X_{i,g,t}$, includes pre-season and growing season total precipitation and evapotranspiration.

[9] Table C.1 contains the estimated average treatment effects from figure 3 expressed in levels for each dependent variable. Tables C.2 and C.3 contain the $\hat{\delta}^{CS}(g)$ estimates of cohort-specific average treatment effects from equation 3. Finally, in table D.3, we report the ATT estimates after limiting each technology transition sub-sample to the period in which the parallel trends pre-test passes.

[10] Figure 1 shows that the average acres irrigated by water right groups with a flood system decreased by more than half from about 200 acres in 1992 to 83 acres in 2019. This could occur if water right groups with fewer acres were the last to adopt center pivots, but that does not appear to be the only driver since irrigated acres for water groups with flood decreased over time before converting to center pivot (Figure A.4).

estimates suggest a 10-40% increase in application efficiency for the conversion from flood to center-pivot irrigation.

We perform two additional analyses of the flood to center pivot conversion to understand the mechanisms driving our ATT results. First, we assess whether differences in behavior between water right groups adopting traditional center pivot systems versus those directly adopting center pivot with LEPA affects our results (table C.4). While the coefficients for the two conversion types have identical signs to those described above, the increase in irrigated acres for the conversion from flood to a center pivot with LEPA is much larger and statistically significant. However, the treatment effects were larger for later cohorts when there was a greater pre-treatment decline in irrigated acreage (table C.2). So, the larger effect of flood to center pivot with LEPA may simply be due to a greater number of these conversions occurring later in the time series (figure A.2).

Second, we use the crop data in the WIMAS records to estimate the effect of switching to center pivot irrigation on the fraction of water right groups' irrigated acreage planted to five crops: alfalfa, corn, soybeans, soy, and wheat. We find statistically significant evidence of water right groups planting more corn and less sorghum after adopting center pivot irrigation (table C.5). After converting to center pivot irrigation, irrigators were able to continue growing the comparatively more water-intensive crop, corn, while those who remained in flood irrigation planted the more drought resistant alternative, sorghum. Even though irrigators planted more water-intensive corn after adopting center pivot irrigation, they still decreased the average depth applied.

The bottom row of panels in figure 3 depicts the average treatment effect results for the transition from traditional center pivot to LEPA irrigation. For all three dependent variables, the

$\hat{\delta}^{CS}$ estimates are negative and statistically insignificant. We estimate a 3.5% (6.8 acre-feet) reduction in groundwater withdrawals following adoption of LEPA with our preferred estimator. The effects of LEPA adoption on irrigated acreage and depth-applied are smaller reductions of 1.2% (2.1 acres) and 1.7% (0.02 feet) respectively.[11] While statistically insignificant, the negative treatment effects estimated for withdrawals and depth-applied are consistent with expectations that increases in application efficiency translate into reductions in groundwater use and do not support the conclusion that LEPA adoption leads to Jevon's paradox. We also find no significant effects of LEPA adoption on the crop choice (table C.5). But, similar to the conversion from flood to center pivot irrigation, the estimated reductions in withdrawals and depth-applied fall short of expected savings given the 5-15% increase in application efficiency predicted by engineering estimates.

[11] In contrast to the transition from flood to center pivot irrigation, the pre-treatment trajectories depicted in figure A.5 for the LEPA adoption transition are closely centered around zero. As such, these estimates represent the effect of adopting LEPA relative to a counterfactual where irrigation behavior remained roughly constant.

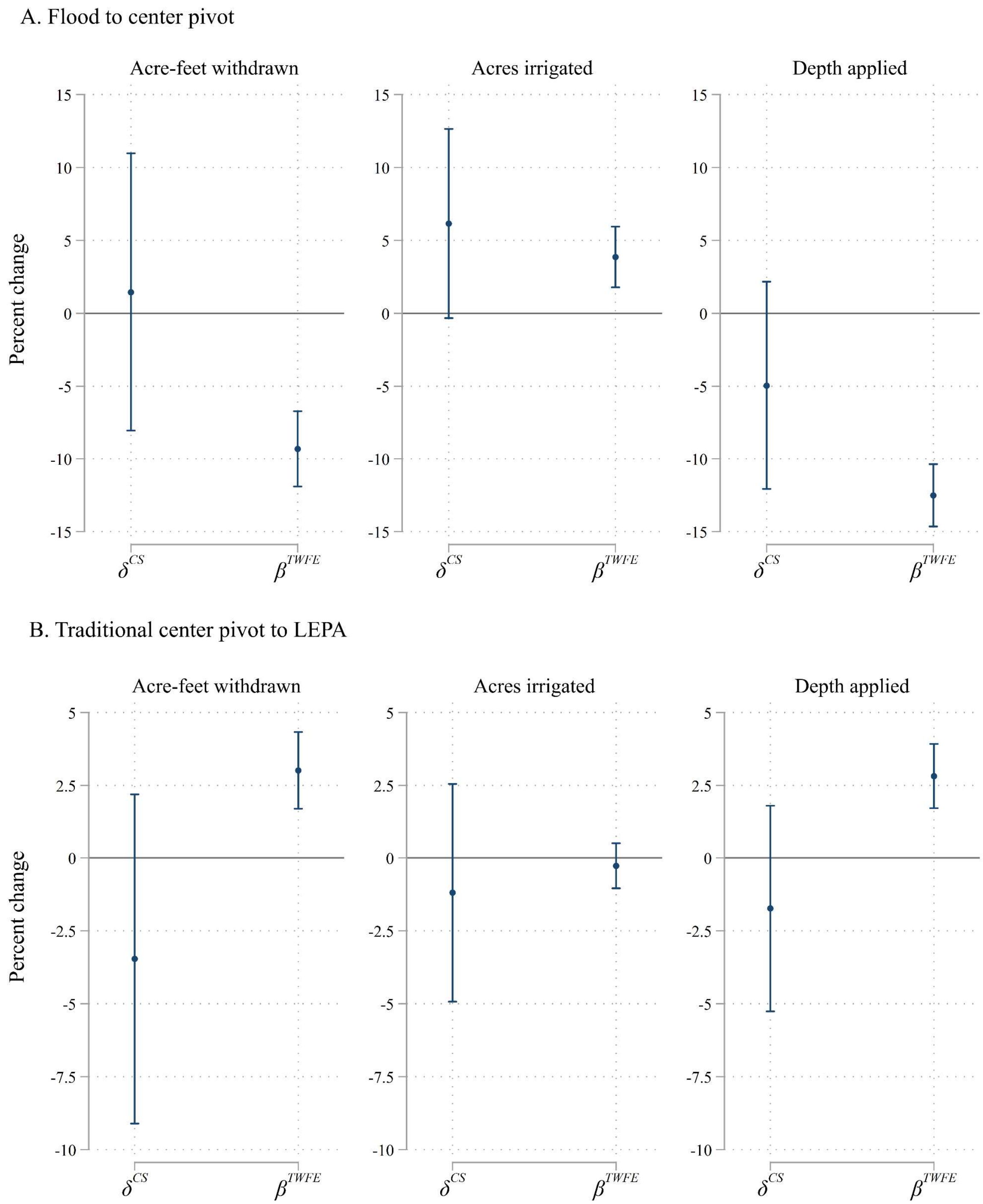

Figure 3: Effect of adopting each technology for our preferred estimator from Callaway and Sant'Anna (2020), δ^{CS}, and two-way fixed effects, β^{TWFE}. Treatment effects are expressed as a percent change relative to the sample mean of each dependent variable. Note, due to the staggered adoption of both irrigation technologies, TWFE estimates may be biased.

5.2 Dynamic treatment effects

We can understand how irrigators adjust to each new irrigation technology by examining how the treatment effects change over time. Figures 4 and 5 display the dynamic treatment effects for the transitions from flood to center pivot irrigation and from traditional center pivot to LEPA irrigation. As in figure 3, the dynamic effects are expressed as a percent change relative to the mean values of the dependent variables in the pertinent sub-sample. Similarly, we discuss the preferred $\hat{\delta}^{CS}(l)$ (equation 4) estimates in figures 4 and 5 in this sub-section and address the biased $\hat{\beta}^{TWFE}(l)$ estimates later.[12] Additional tables of results are provided in Appendix C.[13]

The instantaneous effect of converting from flood to center pivot irrigation, the $\hat{\delta}^{CS}(l)$ estimate at time $l = 0$, is a statistically significant 9.9% (18.9 acre-feet) reduction in groundwater withdrawals (top panel of figure 4). After the initial reduction in withdrawals, the treatment effect steadily trends upward. During the first decade after adoption, the negative or near zero $\hat{\delta}^{CS}(l)$ estimates indicate that groundwater withdrawals among adopters of center pivot irrigation were less than or equal to what they would have been with flood irrigation. Then in subsequent years, adoption of center pivot irrigation resulted in greater withdrawals, which should be interpreted as a smaller reduction in withdrawals over time than would have occurred with flood irrigation.

Irrigated acreage was 4 to 8 percent greater due to the adoption of center pivots during the decade after adoption (middle panel of figure 4). Despite declining groundwater resources,

[12] We use $\hat{\beta}^{TWFE}(l)$ to indicate the effect of changing technologies at time l relative to adoption estimated using the following regression $Y_{i,g,t} = \lambda_{i,g} + \gamma_t + \Phi X_{i,g,t} + \sum_{j=2} \beta_{-j} \left(lead_j\right)_{i,g,t} + \sum_{k=0} \beta_k (lag_k)_{i,g,t} + u_{i,g,t}$, where $\left(lead_j\right)$ is the binary variable indicating if group g is j years before changing technologies in year t and (lag_k) is the binary variable indicating if group g is k years after changing technologies in year t.

[13] The results depicted in figures 4 and 5 are also presented in levels for each dependent variable in Tables C.6 and C.7.

adopters of center pivot irrigation maintained greater irrigated acreage because of the increase in application efficiency. So, we find that adoption of center pivot systems prolonged irrigated agriculture. The increased application efficiency also allowed them to make significant reductions in depth-applied without reducing the water available to their crops (bottom panel of figure 4).

For the transition from traditional center pivot to LEPA irrigation in figure 5, the $\hat{\delta}^{CS}(l)$ estimates indicate water right groups decrease their groundwater withdrawals starting around 7 years after adoption. The $\hat{\delta}^{CS}(l)$ estimate 24 years after adopting LEPA is a statistically significant 19% (38 acre-foot) decrease in groundwater withdrawals (top panel of figure 5). The $\hat{\delta}^{CS}(l)$ estimates for dynamic effects on acres irrigated are all statistically insignificant and they are consistently near zero for 20 years after LEPA adoption (middle panel of figure 5). The $\hat{\delta}^{CS}(l)$ results for depth-applied are also statistically insignificant but depict a similar downward trend over time as withdrawals (bottom panel of figure 5).

For both technology conversions studied here, the dynamic treatment effects we find reveal how irrigators adjust to changes in irrigation technology over time. For the conversion from flood to center pivot irrigation, we observe large reductions in withdrawals immediately after the technology transition. Due to the increase in application efficiency, irrigators who adopted center pivot irrigation could decrease depth-applied and avoid reducing irrigated corn acreage. In contrast, there are no perceptible changes in irrigators' behavior immediately after adopting LEPA. There is evidence that withdrawals decreased for LEPA through the intensive margin about 7 years after adoption, but these effects are mostly statistically insignificant.

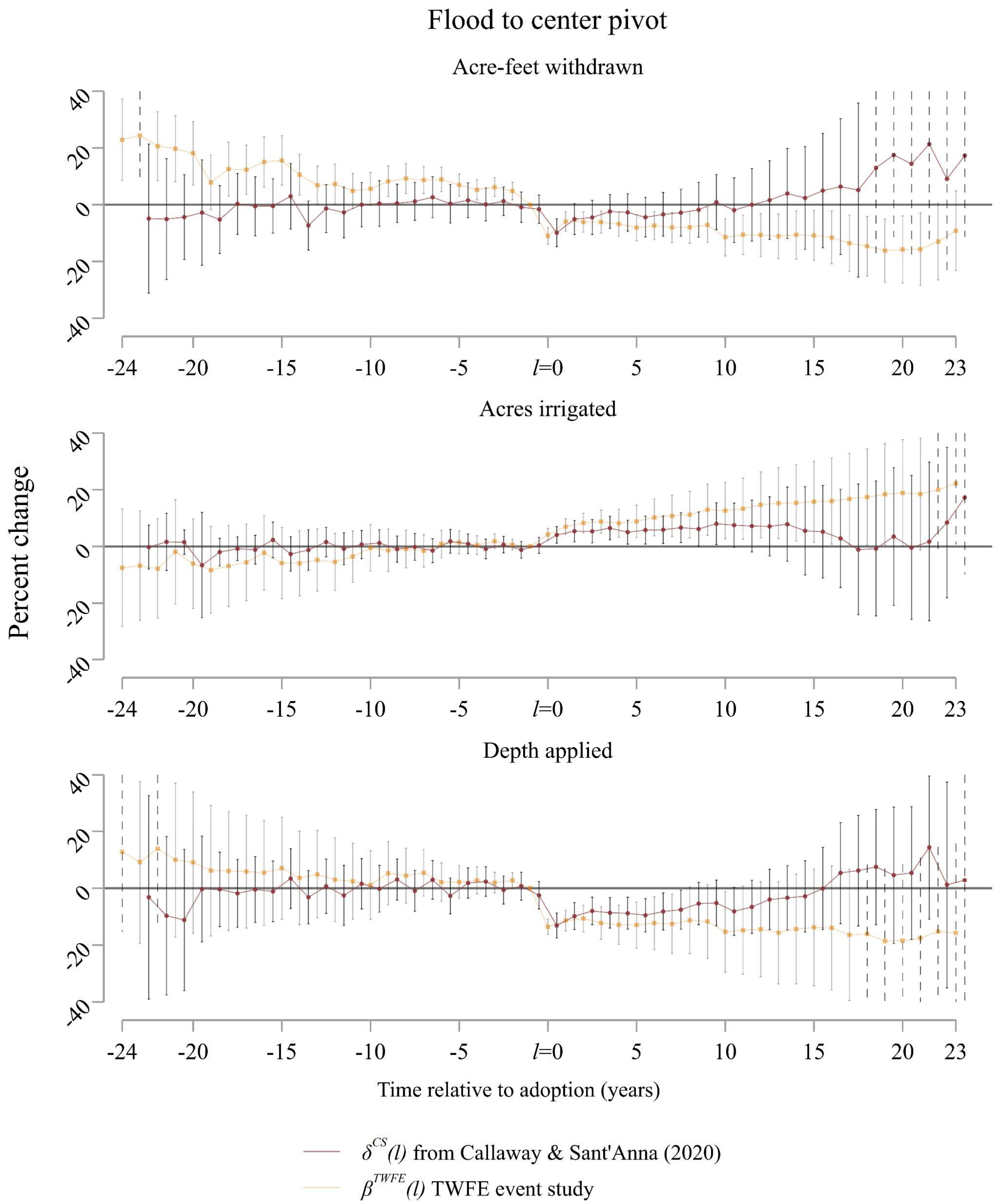

Figure 4: Effect of changing from flood to center pivot irrigation at time l, where l is years relative to when center pivot irrigation is first adopted. Effects are expressed as a percent change relative to the sample mean of each dependent variable. Error bars represent the 95% confidence interval, with dotted lines indicating the confidence interval extends beyond the y-axis range.

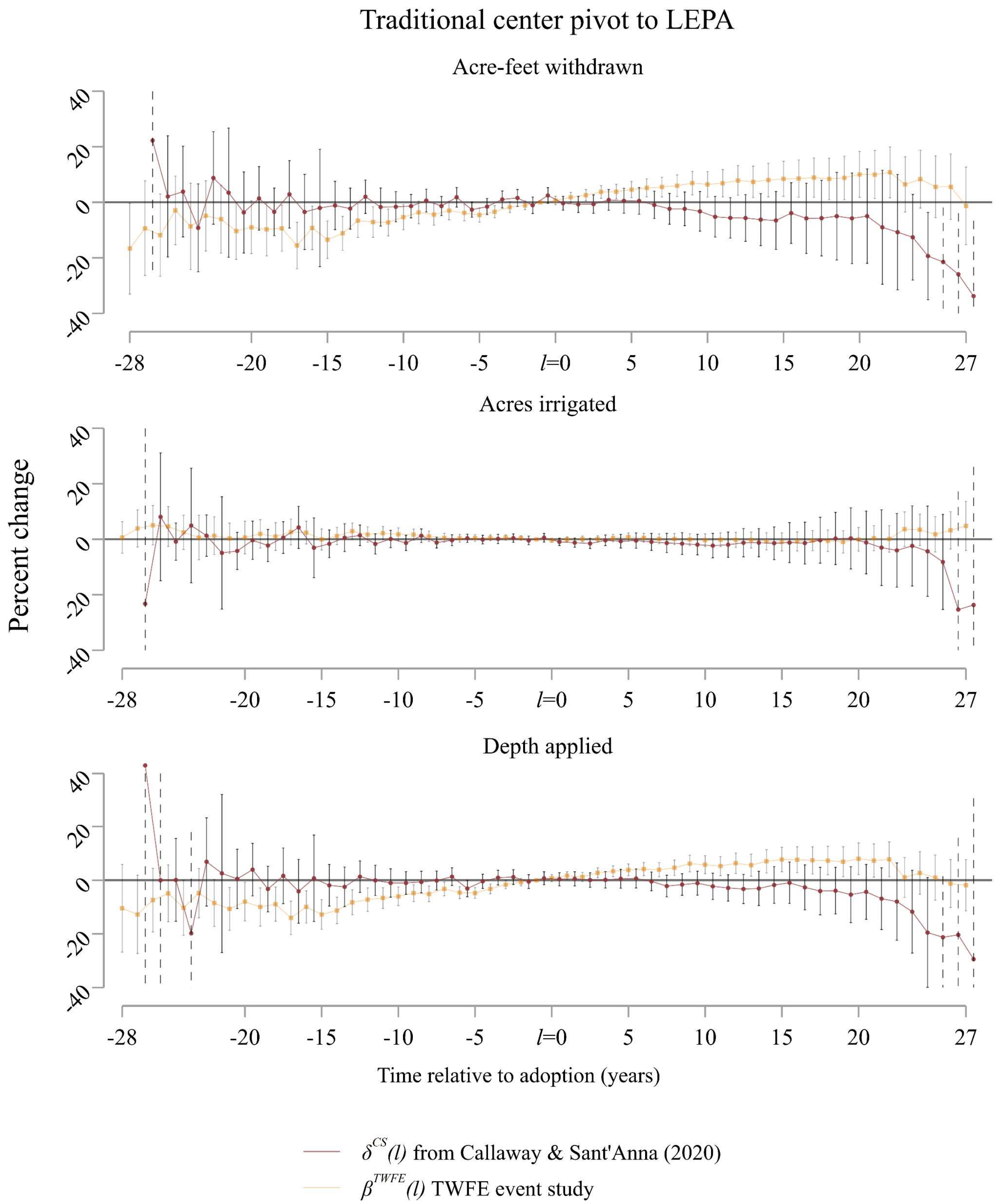

Figure 5: Effect of changing from traditional center pivot to LEPA irrigation at time l, where l is years relative to when LEPA is first adopted Effects are expressed as a percent change relative to the sample mean of each dependent variable. Error bars represent the 95% confidence interval, with dotted lines indicating the confidence interval extends beyond the y-axis range.

5.3 Robustness checks

We perform three checks to test our main results are robust to selecting a different time period, changes in the composition of adoption cohorts, and an alternative difference-in-differences estimator. First, we limit our sub-sample to the years from 1996 to 2005 when the pre-test passes (tables D.1 and D.2). For the conversion from flood to center pivot, the signs of the extensive and intensive margins are the same as our preferred estimate, but they are also statistically significant with the limited sample period (table D.3). Dynamic treatment effects with the limited sample also indicate an immediate reduction in withdrawals after adoption and the effects on irrigated acreage and depth-applied are similar to our preferred estimates (figure D.1). For the conversion from traditional center pivot to LEPA irrigation, we also find a statistically insignificant impact on all dependent variables with the shorter period, though the impact on withdrawals is small (0.9 acre-feet) and positive (table D.3).The downward trend in estimated treatment effects for withdrawals and depth applied beginning 7 years after adoption remains unchanged along with minimal effects on irrigated acres (figure D.2).

Our second robustness check is to ensure our dynamic effect results are robust to changes in the composition of adoption cohorts occurring between 1996 and 2005. To do this, we generate $\delta^{CS}(l)$ estimates using water right groups with at least 2, 4, 6, and 8 years of data after changing technologies. By balancing the sample with respect to “event-time,” we ensure the dynamic treatment effect results are driven by changes in behavior and not by missing data (McCrary 2007; Bailey and Goodman-Bacon 2015). For the change from flood to center pivot, the dynamic treatment effect results after “event-time” balancing also find significant evidence of an instantaneous decrease in groundwater withdrawals, retention of irrigated acreage relative to flood irrigators, and a persistent reduction in irrigation intensity (tables D.4, D.5, and D.6). For traditional center pivot to LEPA, we find largely insignificant impacts except for some evidence of a gradual decrease in depth-applied (tables D.7, D.8, and D.9).

The third robustness check uses an alternative estimator which accommodates staggered adoption and dynamic treatment effect settings described in de Chaisemartin and D'Haultfoeuille (2022). We use $\hat{\delta}^{CD}$ and $\hat{\delta}^{CD}(l)$ to denote estimates for the average and dynamic treatment effect versions of the estimator from de Chaisemartin and D'Haultfoeuille (2022) and provide an in-depth explanation of its formulation and assumptions in Appendix D. The $\hat{\delta}^{CS}$ and $\hat{\delta}^{CD}$ estimates of average treatment effects are similar (figure D.3). For the transition from flood to center pivot irrigation, the $\hat{\delta}^{CD}$ and $\hat{\delta}^{CS}$ estimates have the same signs but the positive effect on acres irrigated for the $\hat{\delta}^{CD}$ estimate is statistically significant. For the change from traditional center pivot to LEPA, the $\hat{\delta}^{CD}$ estimates are close to zero for all three outcomes. Dynamic treatment effects are also similar between $\hat{\delta}^{CD}(l)$ and $\hat{\delta}^{CS}(l)$ (figures D.4 and D.5).

5.4 TWFE results and comparison to prior studies of LEPA adoption

We include a two-way fixed effects specification in our analyses to illustrate the bias which can result from applying TWFE in staggered adoption settings. To demonstrate the degree to which staggered treatment could bias TWFE results, we perform a Goodman-Bacon decomposition on balanced sub-samples using the *bacondecomp* R package (Flack and Jee 2020).[14] The decompositions were produced without including covariates as controls. For both the flood to center pivot and traditional center pivot adopting LEPA transitions, the problematic "Later vs. Earlier Treated" comparisons are given at least twice the weight of the "Earlier vs. Later Treated" comparisons (table B.1 and figure B.4). Given the robust evidence of dynamic

[14] Note, for the flood to center pivot or LEPA transition, we include the "never-treated" water right groups and all years from 1991 to 2019 when performing the decomposition.

treatment effects, the results from the Goodman-Bacon decompositions show that TWFE estimates will be biased.

Comparing the $\hat{\delta}^{CS}$ and $\hat{\beta}^{TWFE}$ estimates of average treatment effects in figure 3 illustrates how the bias of TWFE leads to erroneous conclusions. In the case of flood irrigators switching to center pivot irrigation, the $\hat{\beta}^{TWFE}$ estimate indicates a statistically significant 9.32% reduction in withdrawals due to a large decrease in depth applied, whereas the $\hat{\delta}^{CS}$ estimate indicates a small and statistically insignificant positive effect on withdrawals. The combination of an immediate reduction and then an increasing trend in the dynamic treatment effects for withdrawals (figure 4) leads to the negative bias of TWFE. TWFE compares late adopters' immediate reductions in withdrawals to increases by early adopters occurring at the same time, magnifying the negative $\hat{\beta}^{TWFE}$ estimate of the effect on withdrawals. For the change from traditional center pivot to LEPA irrigation, TWFE produces biased estimates of the wrong sign that are statistically significant due to the evolution of treatment effect dynamics similar to the example in Appendix B. TWFE uses a faulty counterfactual based on the decreasing withdrawals of early adopters, creating upward bias in the $\hat{\beta}^{TWFE}$ estimate.

TWFE estimation of event study specifications are also biased in the staggered adoption setting (Sun and Abraham 2021). For the flood to center pivot transition, the $\hat{\beta}^{TWFE}(l)$ estimates are consistently negative with a slight downward trend in treatment effects for withdrawals and depth applied, while $\hat{\delta}^{CS}(l)$ estimates indicate an upward trend and become positive a decade after adoption (figure D.4).[15] For traditional center pivot to LEPA, the $\hat{\beta}^{TWFE}(l)$ estimates are

[15] In comparison to the $\hat{\beta}^{TWFE}(l)$ estimates, the $\hat{\delta}^{CS}(l)$ results contain one less estimate during the pre-treatment period in figures D.4 and D.5. This is because the standard approach outlined in Callaway and Sant'Anna (2020) employs long-differencing when estimating pre-treatment outcomes, so the pre-treatment dynamic treatment effects can be interpreted as average treatment effects at a given time relative to treatment. In contrast, our TWFE event study specification uses the period one year before adoption as a baseline period.

generally the opposite sign and trend in the opposite direction when compared to the $\hat{\delta}^{CS}(l)$ estimates (figure D.5).

One limitation of our preferred $\hat{\delta}^{CS}$ estimates is that the confidence intervals are larger than those of the $\hat{\beta}^{TWFE}$ estimates. The $\hat{\delta}^{CS}$ estimates are generated using a doubly robust estimator, and doubly robust estimators can be less efficient when the outcome regression or propensity score components are incorrectly specified (Sant'Anna and Zhao 2020). Indeed, the confidence intervals overlap between $\hat{\delta}^{CS}$ and $\hat{\beta}^{TWFE}$ in figure 3. No formal statistical test of the difference between $\hat{\delta}^{CS}$ and $\hat{\beta}^{TWFE}$ estimates has been developed—likely because the TWFE and Callaway and Sant'Anna's (2020) approach recover fundamentally different treatment effect parameters. Nevertheless, the difference between our $\hat{\delta}^{CS}$ and $\hat{\beta}^{TWFE}$ estimates is economically important since the $\hat{\beta}^{TWFE}$ estimates are of the opposite sign, statistically significant, and economically important in magnitude.

Our preferred $\hat{\delta}^{CS}$ results differ from previous studies, most likely due to TWFE bias. Pfeiffer and Lin (2014) and Li and Zhao (2018) both examine the impact of LEPA adoption on groundwater use in Kansas. While neither study uses TWFE as their preferred estimator, both studies employ binary indicators of adoption while accounting for unobserved heterogeneity across units and time. Pfeiffer and Lin (2014) include unit and time fixed effects in an IV estimator. Li and Zhao (2018) include correlated random effects and time fixed effects in a joint dynamic estimation strategy. The Goodman-Bacon decompositions, dynamic treatment effects, and the difference between our $\hat{\delta}^{CS}$ and $\hat{\beta}^{TWFE}$ estimates indicate that the main reason our results differ from these previous studies is bias in TWFE estimates.

Furthermore, our TWFE estimates are similar to results from these previous studies. Our TWFE estimates suggest that the effect of LEPA adoption is a statistically significant 3 percent

(5.91 acre-foot) increase in groundwater withdrawals (figure 3 and table C.1). Pfeiffer and Lin (2014) report a 3 percent increase in withdrawals with their preferred IV specification and with TWFE. Li and Zhao (2018) report a 6-7 acre-foot increases in withdrawals for irrigators with moderately sized water rights. Differences between the period of analysis also do not explain why these previous studies are different from our preferred results because we obtain similar $\hat{\delta}^{CS}$ and $\hat{\beta}^{TWFE}$ estimates with data from the period 1996-2005 that was used by Pfeiffer and Lin (2014) (table D.3).

6 Conclusion

In summary, we find no evidence of Jevon's paradox for the two irrigation technology changes we investigate in this study. The possibility of such a feedback loop by which increasing efficiency encourages additional resource use is certainly cause for concern, but the empirical results presented here do not substantiate claims of its occurrence in the context of groundwater withdrawals. Instead, our results demonstrate how adoption of efficiency improving irrigation technologies enabled irrigators to adapt to changing groundwater conditions over time.

We find irrigators converting from flood to center pivot irrigation avoided reducing irrigated corn acreage by making an immediate reduction in groundwater withdrawals and maintaining a persistent reduction in depth applied. While significant, the 10% reduction in depth-applied we detect during the decade after irrigators adopt center pivot irrigation is the minimum increase in efficiency predicted by engineering estimates. The average treatment effects of LEPA adoption for withdrawals, irrigated acres, and depth-applied are all indistinguishable from zero. Overall, we find that adoption of LEPA resulted in small, marginal adjustments to groundwater use consistent with the comparatively smaller increase in application efficiency predicted by engineering estimates.

Though irrigation technology changes with small efficiency gains may not reduce groundwater withdrawals, such technologies may increase the quantity of crops produced per unit of groundwater extracted. For example, as is suggested by the dynamic effects of LEPA adoption, they may facilitate long-term adaptation that allows producers to maintain yields while reducing groundwater use over time. Alternatively, they could increase the yield produced per unit of water or mitigate risk by reallocating the same quantity of groundwater to better use in a smaller area.

There are two main limitations to our study. First, we do not have detailed information on the application efficiency for each irrigation system in our dataset. Instead, we use engineering estimates of typical ranges to determine whether our estimated changes in withdrawals achieved expected savings. Second, in our study context, groundwater is the dominant source of water for irrigation and the rate of aquifer recharge is often negligible. Future research is needed to determine whether irrigation technology changes produce similar dynamics in contexts reliant on surface water resources or with significant return flows.

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Appendix A - Data processing and sub-sample creation

The initial dataset, containing water right groups using any irrigation system between 1991 and 2019, has a total of 18,541 unique water right groups and 444,678 observations. We remove 3,653 water right groups because they lack location data, meaning we are unable to attach the pertinent pre-development aquifer, soil conditions, or weather variables. An additional 774 water right groups are removed because they lack data on authorized quantities. Removing observations with zero recorded irrigated acres and non-zero values for acre-feet applied does not remove any water right groups entirely, but it does drop 495 observations from the sample. Removing observations with acre-feet withdrawn, acres irrigated, or depth-applied greater than the respective 99th percentile value drops 10,755 observations so there are 352,876 remaining. This also reduces the number of water right groups to 14,038. At this point, we remove the 34,437 observations using any irrigation system aside from flood, center pivot, or LEPA.

There are 13,632 water right groups and a total of 315,439 observations remaining after removing the irrigation technologies not involved in this study. Removing the observations with fractional values for the remaining irrigation systems, in contrast, drops only 19 water right groups and 7,410 observations. In terms of the number of observations excluded, removing water right groups that report multiple transitions into a technology or reverting back from a technology is the largest filter we apply to our dataset. After removing water right groups that report multiple switches or reversions in irrigation technology, there are 8,562 water right groups remaining with a total of 181,052 observations between them.

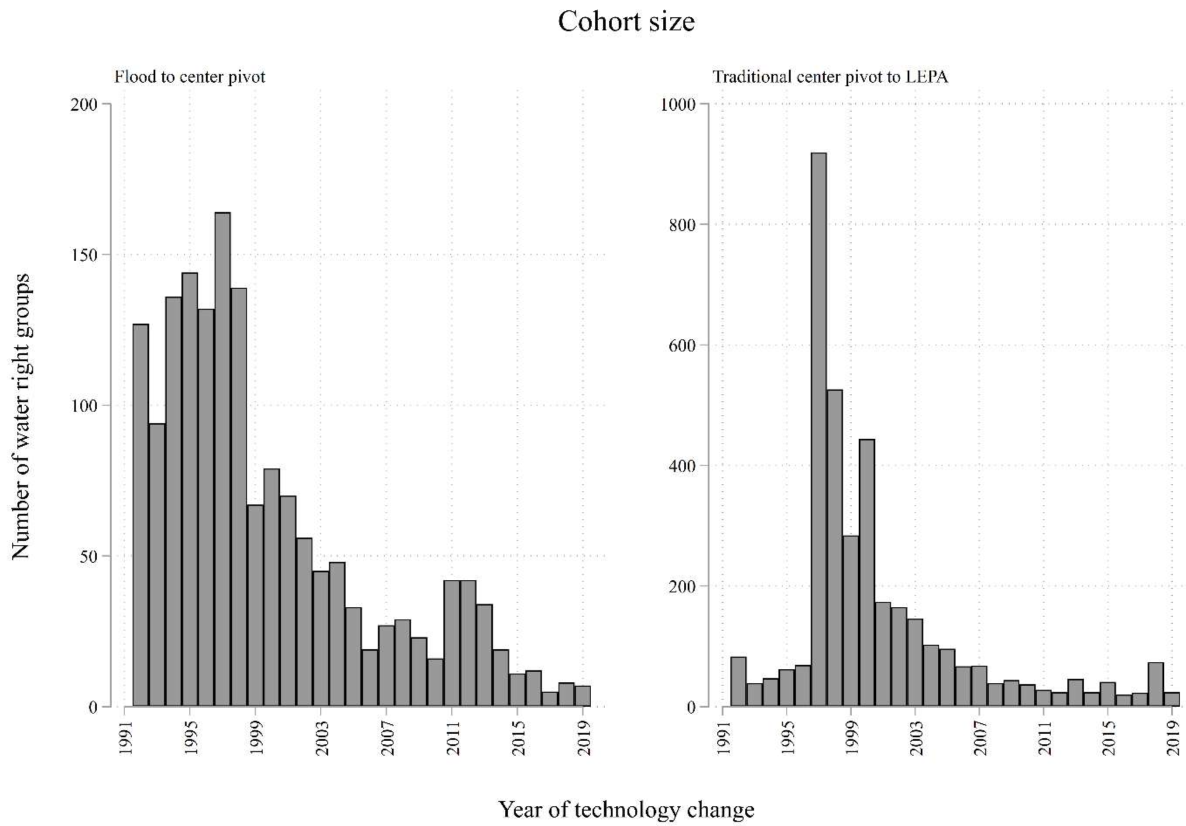

Figure A.1: Number of water right groups changing irrigation technologies in a given year for each sub-sample.

Cohort size

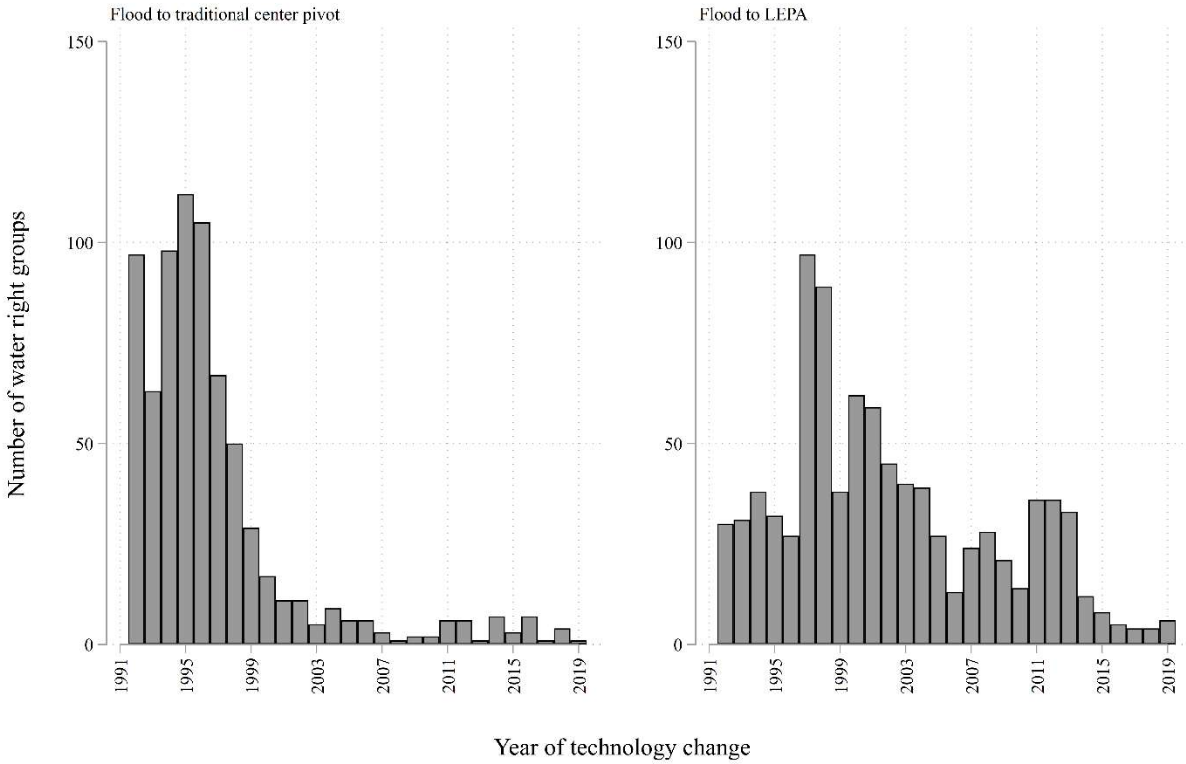

Figure A.2: Number of water right groups in flood to center pivot sub-sample who change to a traditional center pivot irrigation system without LEPA devices and to a center-pivot system with LEPA devices by year.

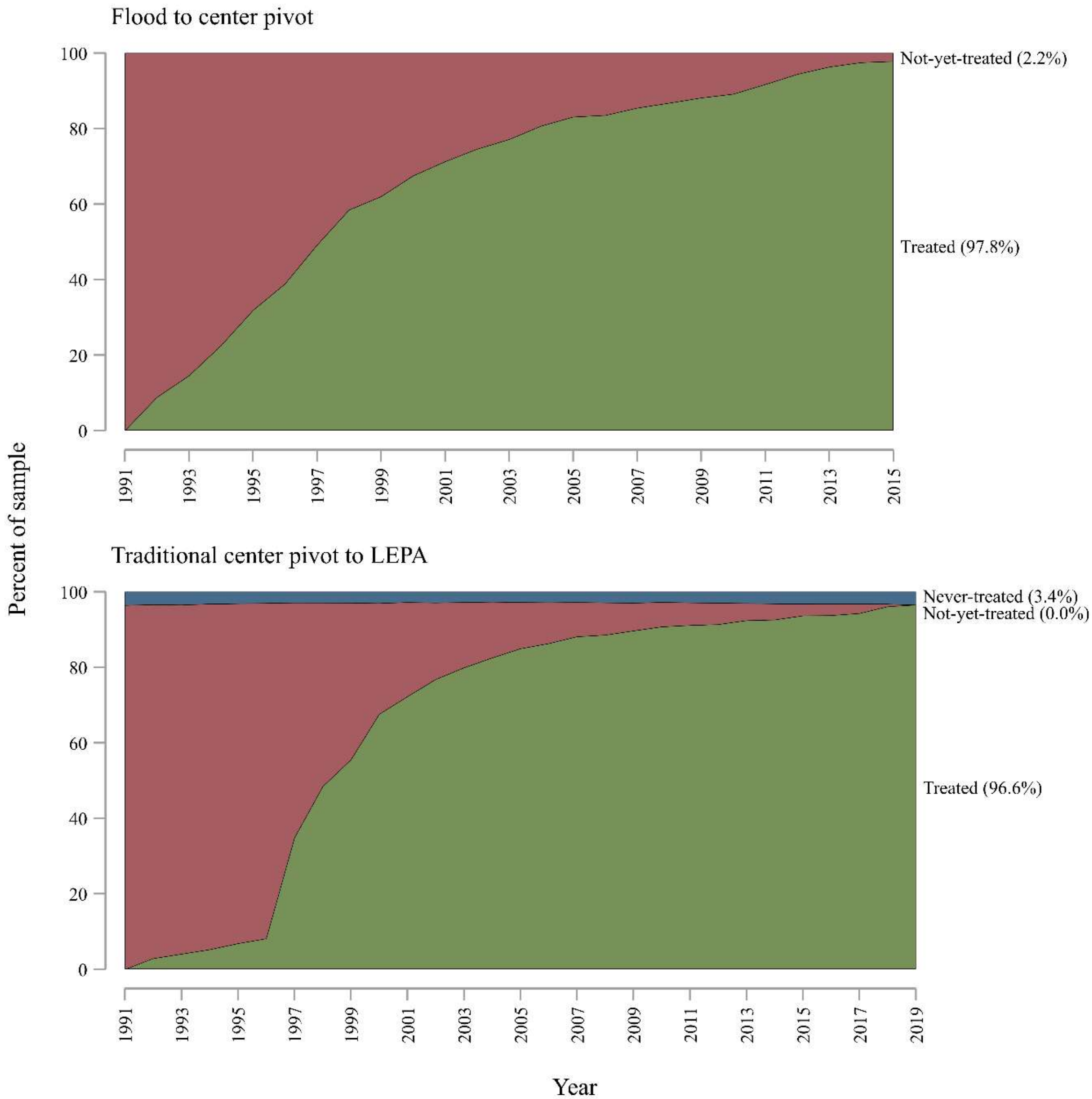

Figure A.3: Treatment status of water right groups over time in each technology change subsample.

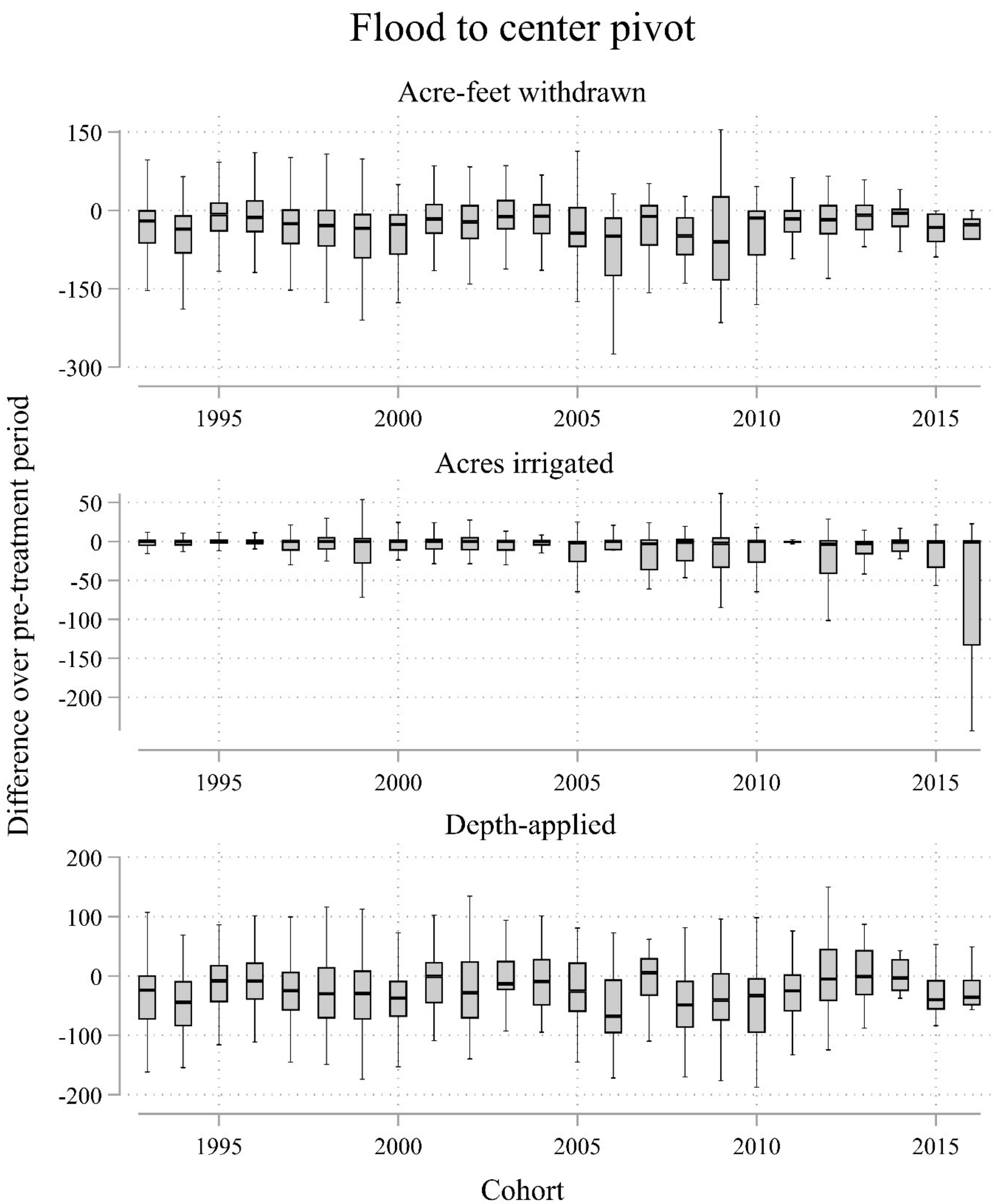

Figure A.4: Boxplots of the changes in three groundwater use outcomes over the pre-adoption time period by adoption cohort for the flood to center pivot transition.

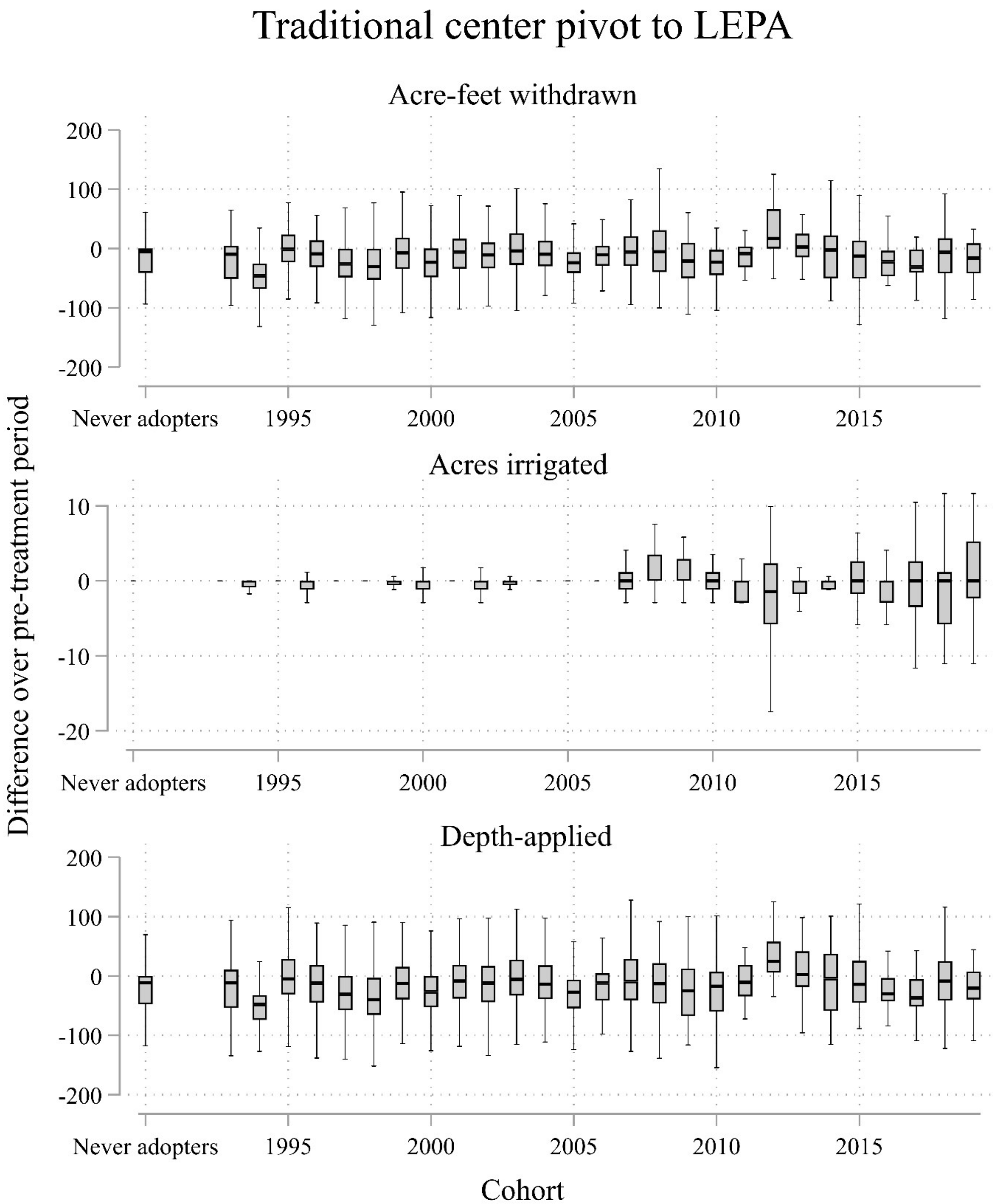

Figure A.5: Boxplots of the changes in three groundwater use outcomes over the pre-adoption time period by adoption cohort for the center pivot adopting LEPA transition. For the never adopters, water right groups that never install LEPA devices in our study period, the value from the earliest observation is subtracted from that of the latest.

Appendix B - Potential TWFE bias and diagnostics

Consider a collection of irrigators with an opportunity to invest in a more efficient technology at any period, t, before the last period in the panel dataset, T. For the following demonstration, let $T = 3$. We consider three groups (or cohorts) of irrigators indexed by the subscript g which indicates the first year in which they adopted the new technology. Additionally, let the indicator variable, $G_{i,g}$, indicate the year in which a group is first treated by taking a value of one if irrigator i is first treated in period g. The first group of irrigators (i.e., early adopters), adopt the more efficient technology at the beginning of the second season such that $g = 2$ and $G_{i,2} = 1$ for irrigators in this group. The second group (i.e., late adopters), adopt the more efficient technology at the beginning of the third season meaning $g = 3$ and $G_{i,3} = 1$. The last group of irrigators do not adopt the new technology in any of the observed years (i.e., never adopters), so we set their group index to the period after the end of the panel dataset such that $g = 4$ and $G_{i,4} = 1$.

The outcome of interest, $Y_{i,g,t}$, is the acre-feet of groundwater withdrawn by irrigator i in group g for year t, and the treatment effect we want to recover is the average change in groundwater extraction that occurred by time T due to irrigators adopting the more efficient technology. To express this average treatment effect (ATE), we represent irrigation technology adoption status using a binary variable, $D_{i,g,t}$, that takes a value of 1 for every period in which the respective irrigator has adopted the newer, more efficient irrigation technology. Then, as each observation within a group has an identical treatment sequence, meaning $D_{i,g,t} = D_{g,t}$ within group g, we represent the treatment path for all groups $g \in 2,3,4$ as $D_g = \{D_{g,1}, D_{g,2}, D_{g,3}\}$. As an example, the treatment sequence for the early adopters is written: $D_2 = \{0, 1, 1\}$. We define $Y_{i,g,t}(D_g)$ as the potential outcome for irrigator i in group g at time t if it experienced treatment trajectory D_g, a modification to the potential outcomes framework of Callaway and Sant'Anna (2020). Lastly, we define N_g as the number of irrigators in group g and N_s as the total number of irrigators who adopt the more efficient technology before the end of the panel. We can then express the average treatment effect in year T as the weighted average of the treatment effects for early and late adopters:

$$ATE = \frac{N_2}{N_s} E\left[Y_{i,2,3}(D_2) - Y_{i,2,3}(D_4)\right] + \frac{N_3}{N_s} E\left[Y_{i,3,3}(D_3) - Y_{i,3,3}(D_4)\right] \quad \text{(B.1)}$$

However, we cannot compute the ATE in equation B.1 because we do not observe the counterfactual outcome evolutions $Y_{i,2,3}(D_4)$ and $Y_{i,3,3}(D_4)$ for the early and late adopters respectively. A difference-in-differences (DD) identification strategy effectively imputes these counterfactual outcomes, where adoption of the technology is considered as the "treatment." The crucial parallel trends assumption requires irrigators who adopt the new technology to have the same change in the dependent variable as those that do not adopt in the counterfactual scenario where the adopters do not actually adopt. Using this assumption, we can rewrite equation B.1 as the following difference-in-differences estimand using observable outcomes:

$$ATE^{DD} = \frac{N_2}{N_s} E\left[\left(Y_{i,2,3}(D_2) - Y_{i,2,1}(D_2)\right) - \left(Y_{i,4,3}(D_4) - Y_{i,4,1}(D_4)\right)\right] + \frac{N_3}{N_s} E\left[\left(Y_{i,3,3}(D_3) - Y_{i,3,1}(D_3)\right) - \left(Y_{i,4,3}(D_4) - Y_{i,4,1}(D_4)\right)\right]. \quad \text{(B.2)}$$

With the effect of interest defined and identification strategy selected, we now specify the groundwater extraction behavior for the three groups and demonstrate how two-way fixed effects estimation fails to recover the ATE. Parameter values are chosen to illustrate that the bias can be large enough to reverse the sign of TWFE estimates in a plausible scenario. At time $t = 1$, irrigators in the early adopter, late adopter, and control groups apply 160, 165, and 170 acre-feet of groundwater each year respectively. Both groups of adopters decrease their groundwater withdrawals by two acre-feet in their first season using the more efficient technology, and the early adopters reduce their withdrawals by an additional 18 acre-feet in their second season post-adoption. The cumulative reduction of 20 acre-feet worth of groundwater represents a 12.5% decrease in withdrawals for the early adopters. Lastly, for simplicity, we assume irrigators in the early and late adopter groups would have maintained their respective initial levels of groundwater use in the counterfactual scenario with no adoption of the more efficient technology. Figure B.1 displays the described scenario graphically.

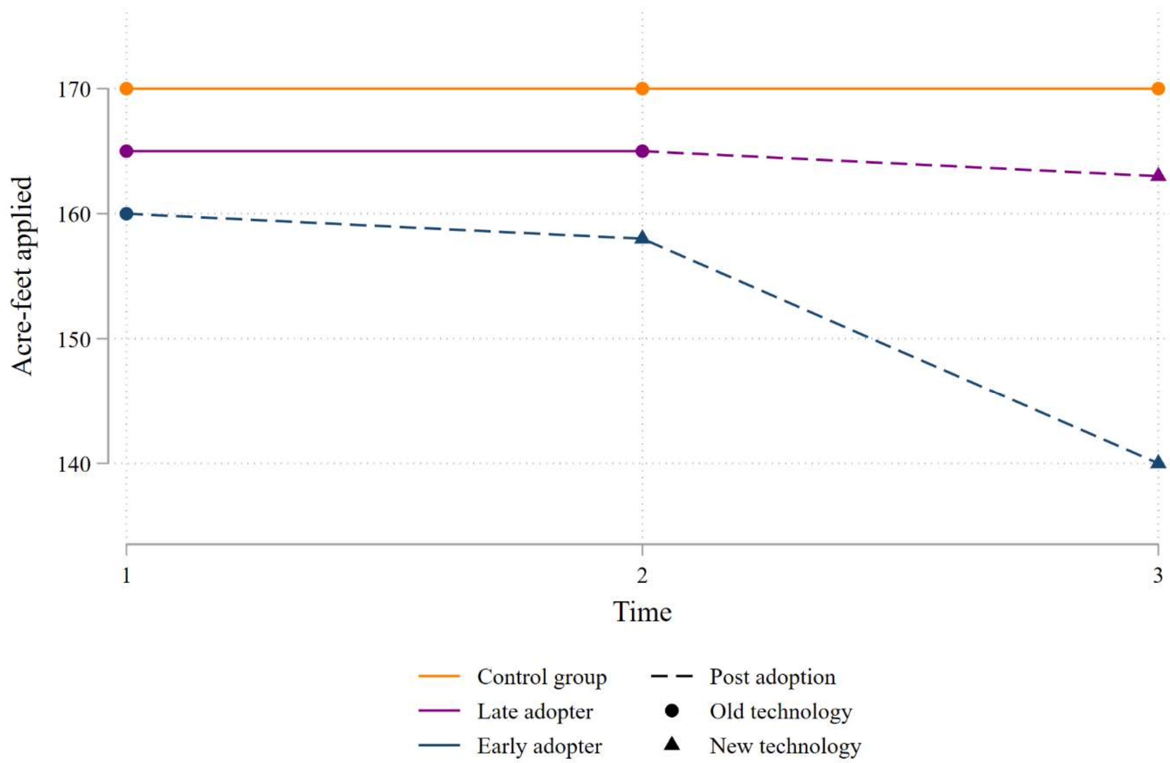

Figure B.1: Hypothetical irrigator water use behavior with two treatment cohorts. The early group adopts the new technology in the season preceding time $t = 2$ and the late group adopts the technology in the season before time $t = 3$.

As each unique combination of i and g comprises a panel unit, we can produce the following linear unobserved effects panel data model with time and unit fixed effects:

$$Y_{i,g,t} = \delta_{i,g} + \gamma_t + \beta^{DD} D_{i,g,t} + u_{i,g,t}. \tag{B.3}$$

We use two-way fixed effects in this hypothetical staggered adoption setting to demonstrate, both graphically and numerically, the source of the bias which can occur using such specifications. Estimating equation B.3 using fixed-effects estimation produces a biased estimate of the ATE because of the staggered nature of adoption, even though the parallel trends assumption holds. As demonstrated by the Difference-in-Difference Decomposition Theorem of Goodman-Bacon (2021), the two-way fixed effects estimator for $\hat{\beta}^{DD}$ is a weighted average of simpler two-by-two difference-in-differences (DD) estimators including two erroneous comparisons between early and later adopters of the new technology. Figure B.2 displays a Goodman-Bacon style decomposition of the four difference-in-differences estimates used by the two-way fixed effects estimator. In figure B.2, panel (a) is a DD using never-adopters as the control for late adopters, panel (b) uses never adopters as the control for early adopters, panel (c) uses late adopters as a control for early adopters before late adopters adopt, and panel (d) uses early adopters as a control for late adopters when late adopters adopt.

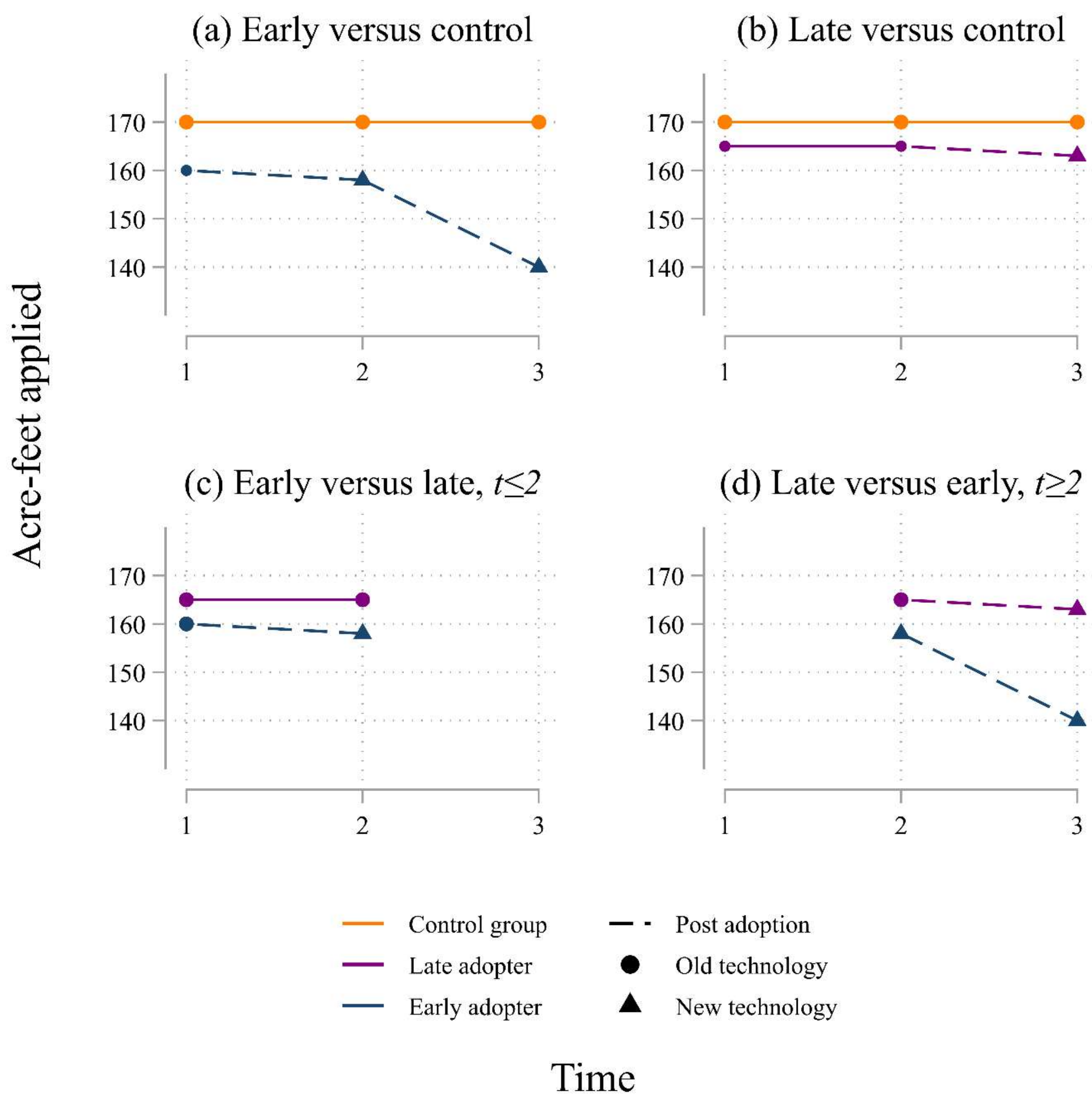

Figure B.2: Decomposition of the two-way fixed effects estimator applied to the staggered adoption example displayed in figure B.1. Panel (d) displays the problematic use of early adopters as the control group for late adopters.

The treatment effect estimated from the DD scenario displayed in panels (a), (b), and (c) of figure B.2 recover the true average treatment effect (ATT) for each of the treated cohorts at their respective times. However, the treatment effect estimated by the DD in panel (d) is biased because it uses the faulty counterfactual outcome produced using the early adopters' outcome trajectory. In fact, panel (d) gives the illusion of a positive treatment effect because the late adopter (i.e., the treated) decreases water use less than the early adopter (i.e., the control). The weights for each DD in figure B.2 used to create the two-way fixed effect estimate depend on the variance of the fixed-effects-adjusted independent variable and the subsample size in each comparison. As such, the size of the early and late adopter groups and the variation in treatment effects amongst them will determine how heavily the problematic DD in panel (d) of figure B.2 is weighted (Słoczynski 2020; Goodman-Bacon 2021). If weighted heavily enough, the incorrectly signed DD estimate in this example would suggest Jevon's paradox occurs for this technology adoption, despite the exact opposite being true.

To numerically demonstrate the bias introduced by improperly applying TWFE estimation, we conduct a Monte Carlo simulation of the scenario outlined above and depicted in figure B.1. We conduct one thousand replications of the simulation where each observation includes a random noise term with mean zero and a standard deviation of one. There are a total of 300 irrigators in the panel dataset we simulate with 50 early adopters, 200 later adopters, and 50 never-adopters. The distribution of estimates for $\hat{\beta}^{DD}$ produced by applying the estimating equation in equation B.3 to each simulation run are displayed in figure B.3 below. Across the 1,000 replications, the average of the TWFE coefficients for $\hat{\beta}^{DD}$ indicates a one acre-foot *increase* in groundwater withdrawals with a standard deviation of 0.14 acre-feet. However, using equation (B.1), the true average treatment effect in year T given these group sizes is $\frac{50}{250}[140 - 160] + \frac{200}{250}[163 - 165] = -5.6$ acre-feet. I

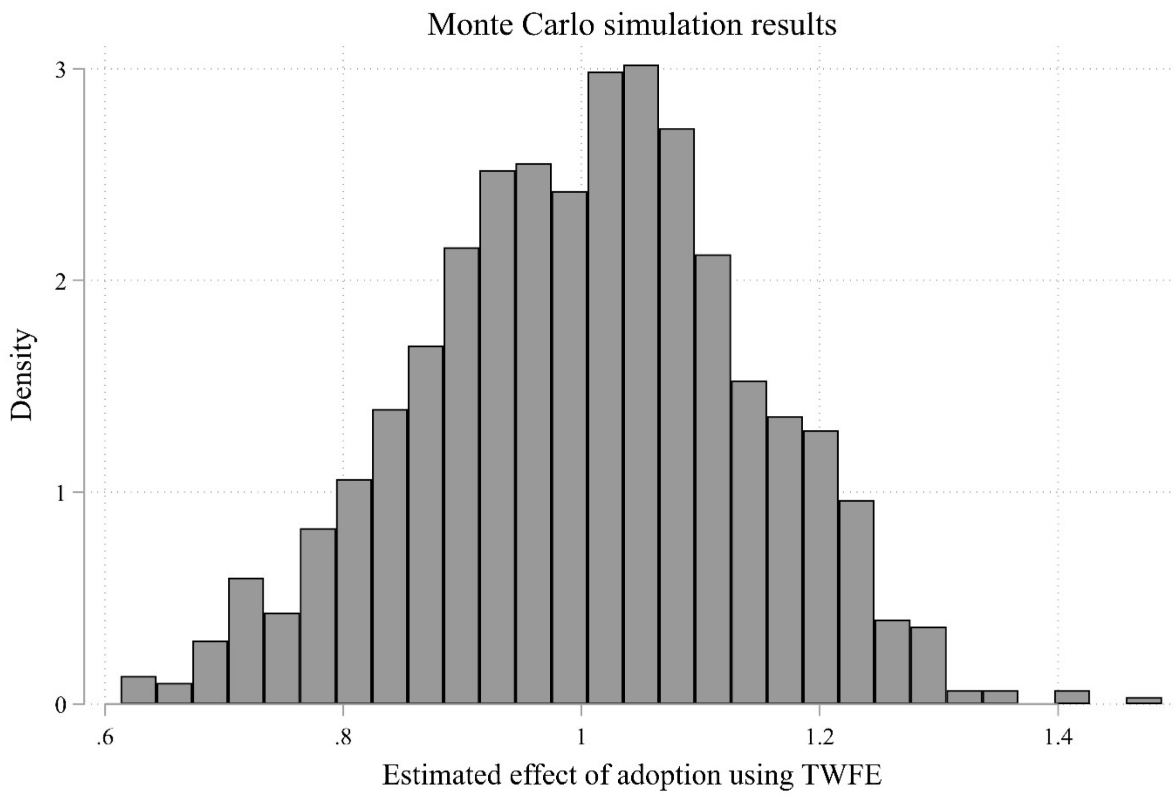

Figure B.3: Distribution of estimates produced by applying the two-way fixed effects estimating equation in equation (B.3) to the staggered adoption example depicted in figure B.2.

Table B1: Bacon-decomposition results for each technology transition and dependent variable combination. Technology transition sub-panels were balanced before performing decomposition. Flood to center pivot/LEPA transition includes "never-treated" water right groups and all years from 1991 to 2019.

	Weight	Weighted average estimate
Flood to center pivot/LEPA		
Total withdrawals (AF)		
Earlier vs. Later Treated	0.18	-5.82
Later vs. Earlier Treated	0.59	-17.91
Treated vs. Untreated	0.23	-3.28
Irrigated acres		
Earlier vs. Later Treated	0.18	5.5
Later vs. Earlier Treated	0.59	2.56
Treated vs. Untreated	0.23	8.41
Depth applied (ft)		
Earlier vs. Later Treated	0.18	-0.09
Later vs. Earlier Treated	0.59	-0.13
Treated vs. Untreated	0.24	-0.07
Traditional center pivot to LEPA		
Total withdrawals (AF)		
Earlier vs. Later Treated	0.32	3.9
Later vs. Earlier Treated	0.62	4.61
Treated vs. Untreated	0.06	20.43
Irrigated acres		
Earlier vs. Later Treated	0.32	-1.44
Later vs. Earlier Treated	0.62	-0.4
Treated vs. Untreated	0.06	-0.58
Depth applied (ft)		
Earlier vs. Later Treated	0.32	0.03
Later vs. Earlier Treated	0.62	0.03
Treated vs. Untreated	0.06	0.09

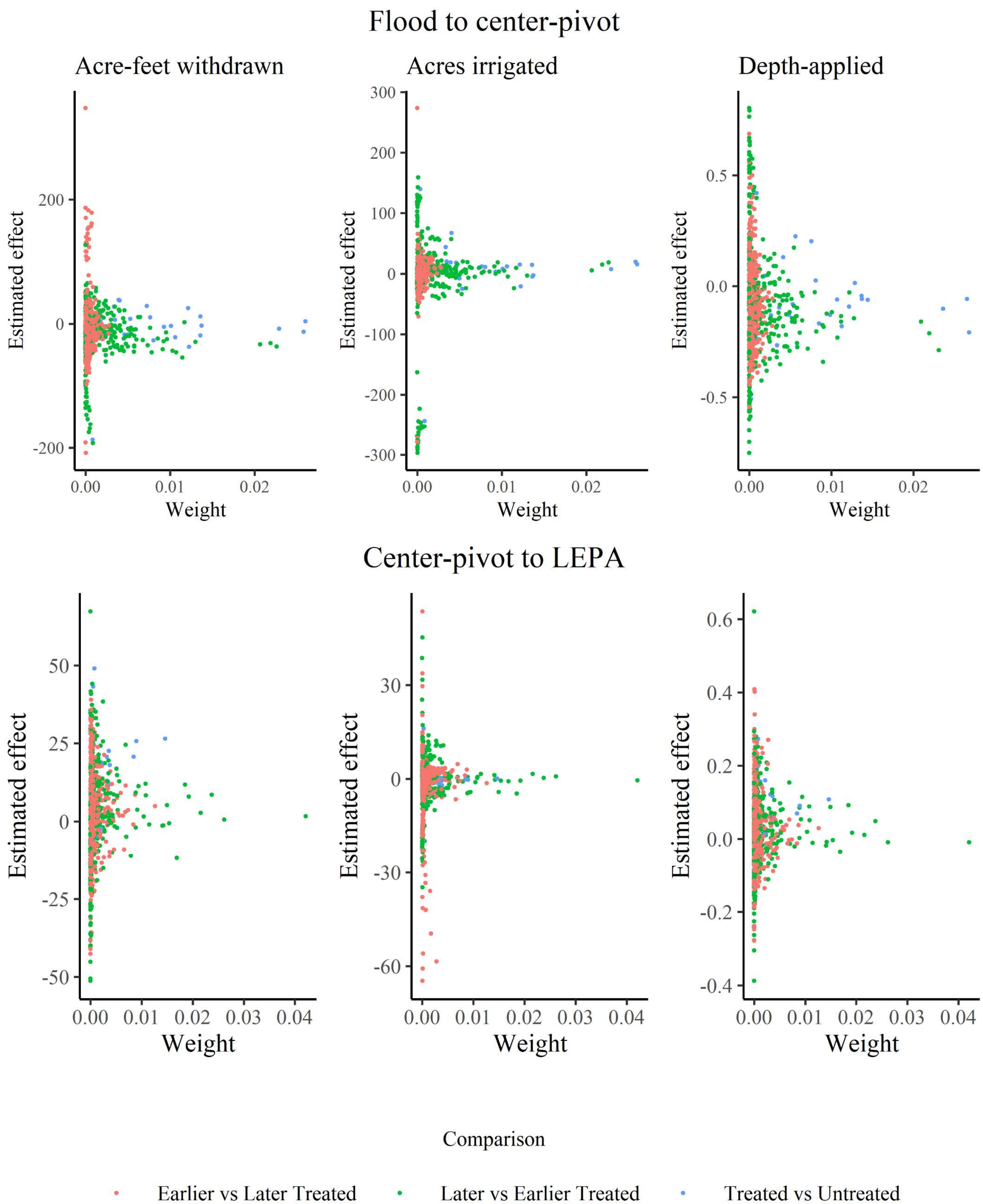

Figure B.4: Bacon decomposition results for the impact of each technology change on the three groundwater use variables. Each point represents a two-by-two comparison of two cohorts.

Appendix C - Additional results tables

Table C.1: Estimated average treatment effect for each technology change in levels for all dependent variables using the full time periods for each sub-sample. Asterisks indicates 95% confidence interval does not contain zero.

Technology transition	Estimator	Dependent variable		
		Acre-feet withdrawn	Acres irrigated	Depth-applied
Flood to center pivot	Callaway and Sant'Anna (2020)	2.79 (-14.66, 20.23)	10.31 (-0.55, 21.16)	-0.06 (-0.14, 0.03)
	TWFE	-17.90* (-22.86, -12.95)	6.47* (2.99, 9.95)	-0.14* (-0.17, -0.12)
Traditional center pivot to LEPA	Callaway and Sant'Anna (2020)	-6.78 (-17.29, 3.72)	-2.07 (-8.58, 4.44)	-0.02 (-0.06, 0.02)
	TWFE	5.91* (3.33, 8.5)	-0.47 (-1.82, 0.87)	0.03* (0.02, 0.04)

Table C.2: Cohort-specific average effect of converting from flood to center pivot irrigation estimated using Callaway and Sant'Anna (2020) approach and aggregation specified in equation 2. Asterisks indicates 95% confidence interval does not contain zero.

Adoption Cohort	Acre-feet withdrawn	Acres irrigated	Depth-applied
1992	8.11	13.12	-0.02
	(-12.24, 28.47)	(-5.66, 31.9)	(-0.18, 0.13)
1993	-8.69	13.27	-0.09
	(-64.35, 46.97)	(-16.15, 42.69)	(-0.31, 0.12)
1994	9.15	-6.47	0.05
	(-29.88, 48.17)	(-34.61, 21.68)	(-0.14, 0.24)
1995	2.72	2.63	-0.08
	(-31.98, 37.42)	(-19.88, 25.13)	(-0.23, 0.08)
1996	-6.85	13.84	-0.09
	(-43.61, 29.9)	(-7.18, 34.86)	(-0.27, 0.09)
1997	-13.9	13.07	-0.18
	(-50.09, 22.28)	(-9.84, 35.97)	(-0.35, -0.02)
1998	-15.94	4.7	-0.08
	(-60.99, 29.11)	(-20.59, 29.99)	(-0.27, 0.12)
1999	13.89	24.03	-0.06
	(-35.77, 63.55)	(-16.79, 64.85)	(-0.29, 0.16)
2000	12.24	20.71	-0.05
	(-21.17, 45.65)	(-5.76, 47.17)	(-0.25, 0.14)
2001	4.89	8.45	-0.06
	(-40.52, 50.31)	(-12.84, 29.74)	(-0.31, 0.19)
2002	40.01	10.99	0.12
	(-5.47, 85.49)	(-19.21, 41.19)	(-0.15, 0.38)
2003	-32.14	-5.47	-0.01
	(-100.09, 35.8)	(-38.67, 27.72)	(-0.31, 0.28)
2004	-3.99	6.18	-0.02
	(-36.54, 28.56)	(-15.62, 27.98)	(-0.27, 0.22)
2005	-22.47	9.14	-0.07
	(-76.41, 31.46)	(-31.97, 50.25)	(-0.42, 0.27)
2006	31.08	-7.69	0.18
	(-32.61, 94.77)	(-69.79, 54.4)	(-0.13, 0.5)
2007	14.36	11.57	-0.04
	(-49.09, 77.82)	(-57.22, 80.36)	(-0.35, 0.28)
2008	45.57	20.94	0.00
	(-12.13, 103.27)	(-5.5, 47.38)	(-0.31, 0.32)
2009	6.00	-15.38	0.00
	(-79.91, 91.91)	(-59.71, 28.95)	(-0.46, 0.45)
2010	66.15	54.51*	0.2
	(12.14, 120.17)	(3.55, 105.46)	(-0.19, 0.58)
2011	18.11	10.11	0.01
	(-22.41, 58.62)	(-16.62, 36.84)	(-0.3, 0.32)
2012	49.40*	31.06*	0.02
	(4.36, 94.44)	(2.25, 59.88)	(-0.32, 0.35)

Table C.2 (continued)

2013	-4.29	18.77	-0.22
	(-46.09, 37.50)	(-12.8, 50.34)	(-0.52, 0.07)
2014	-23.40	27.07	-0.41
	(-71.56, 24.76)	(-7.99, 62.13)	(-0.88, 0.07)
2015	14.06	39.43	-0.41
	(-98.84, 126.96)	(-27.67, 106.52)	(-1.27, 0.45)

Table C.3: Cohort-specific average effect of changing from traditional center pivot to LEPA irrigation estimated using Callaway and Sant'Anna (2020) approach and aggregation specified in equation 2. Asterisks indicates 95% confidence interval does not contain zero.

Adoption Cohort	Acre-feet withdrawn	Acres irrigated	Depth-applied
1992	-34.46	-18.87	-0.09
	(-66.75, -2.17)	(-44.14, 6.41)	(-0.31, 0.12)
1993	-47.65	-7.49	-0.27
	(-81.86, -13.44)	(-46.88, 31.89)	(-0.58, 0.04)
1994	14.13	10.49	0.04
	(-22.4, 50.65)	(-8.07, 29.05)	(-0.13, 0.22)
1995	-2.89	-10.3	0.01
	(-50.39, 44.62)	(-25.8, 5.19)	(-0.17, 0.18)
1996	7.34	-0.91	0.1
	(-22.23, 36.92)	(-28.61, 26.79)	(-0.08, 0.27)
1997	-10.46	-3.22	-0.06
	(-31.1, 10.17)	(-12.78, 6.35)	(-0.13, 0.02)
1998	4.81	3.88	-0.01
	(-16.14, 25.76)	(-8, 15.77)	(-0.09, 0.07)
1999	-4.91	-4.05	0.01
	(-29.4, 19.57)	(-17.66, 9.56)	(-0.09, 0.10)
2000	-1.8	-0.45	0.04
	(-24.98, 21.38)	(-11.81, 10.91)	(-0.06, 0.14)
2001	-9.14	-3.99	-0.02
	(-36.29, 18)	(-16.84, 8.86)	(-0.14, 0.10)
2002	-8.38	-0.55	-0.03
	(-37.62, 20.86)	(-13.28, 12.17)	(-0.16, 0.1)
2003	-15.06	-8.56	-0.05
	(-39.47, 9.36)	(-20.54, 3.42)	(-0.19, 0.08)
2004	-23.99	-5.76	-0.04
	(-53.77, 5.79)	(-17.09, 5.57)	(-0.18, 0.09)
2005	-18.64	-7.69	-0.03
	(-52.4, 15.12)	(-19.06, 3.68)	(-0.15, 0.10)
2006	-1.47	-0.55	0.01
	(-28.33, 25.39)	(-10.53, 9.43)	(-0.12, 0.15)
2007	-1.8	-1.06	-0.01
	(-24.08, 20.48)	(-19.8, 17.68)	(-0.17, 0.15)

Table C.3 (continued)

2008	-14.06	-4.71	-0.04
	(-59.36, 31.25)	(-24.53, 15.12)	(-0.28, 0.21)
2009	-9.29	8.87	-0.01
	(-55.07, 36.48)	(-16.08, 33.82)	(-0.2, 0.19)
2010	-13.5	6.34	-0.05
	(-78.17, 51.17)	(-19.83, 32.51)	(-0.26, 0.17)
2011	6.31	-4.41	0.04
	(-17.72, 30.33)	(-30.41, 21.59)	(-0.18, 0.26)
2012	-20.92	-14.89	-0.02
	(-65.54, 23.7)	(-50.41, 20.63)	(-0.31, 0.28)
2013	-0.75	-5.88	0.00
	(-36.79, 35.28)	(-24.82, 13.06)	(-0.18, 0.18)
2014	0.07	19.98	-0.06
	(-40.97, 41.11)	(-35.51, 75.48)	(-0.31, 0.19)
2015	1.59	7.51	-0.07
	(-33.63, 36.81)	(-17.31, 32.33)	(-0.26, 0.11)
2016	-52.97	7.44	0.00
	(-233.8, 127.86)	(-28.41, 43.29)	(-0.35, 0.35)
2017	-18.42	-20.76	-0.01
	(-55.23, 18.4)	(-62.03, 20.51)	(-0.27, 0.25)
2018	6.24	0.08	0.02
	(-21.37, 33.85)	(-26.94, 27.09)	(-0.13, 0.18)
2019	9.55	-1.96	0.16
	(-31.21, 50.31)	(-55.2, 51.28)	(-0.12, 0.44)

Table C.4: Estimated average treatment effect of converting from flood to center pivot irrigation by whether the water right group switched to a traditional center pivot or a center pivot with LEPA. Asterisks indicates 95% confidence interval does not contain zero.

Technology transition and years used	Estimator	Dependent variable		
		Acre-feet withdrawn	Acres irrigated	Depth-applied
Flood to traditional center pivot without LEPA (1991-2000)	Callaway and Sant'Anna (2020)	-15.06 (-32.48, 2.35)	1.63 (-8.08, 11.34)	-0.02* (-0.18, -0.01)
Flood to center pivot with LEPA (1996-2005)	Callaway and Sant'Anna (2020)	-9.03 (-25.04, 6.98)	11.17* (3.18, 19.16)	-0.12* (-0.20, -0.05)

Note: Analyses were limited to the listed time periods listed because of small cohort size issues.

Table C.5: Estimated average treatment effect of each technology conversion on the fraction of water right groups' irrigated acreage planted to five crops. Asterisks indicates 95% confidence interval does not contain zero.

Technology transition	Estimator	Effect on fraction of water right group irrigated acres planted to listed crop				
		Alfalfa	Corn	Sorghum	Soy	Wheat
Flood to center pivot	Callaway and Sant'Anna (2020)	0.00 (-0.03, 0.03)	0.08* (0.02, 0.13)	-0.04* (-0.08, -0.01)	0.01 (-0.01, 0.04)	0.01 (-0.02, 0.04)
Traditional center pivot to LEPA	Callaway and Sant'Anna (2020)	-0.00 (-0.03, 0.02)	-0.03 (-0.07, 0.02)	0.01 (-0.01, 0.02)	0.01 (-0.01, 0.04)	0.00 (-0.02, 0.02)

Table C.6: Estimated dynamic treatment effects for the transition from flood to center pivot irrigation produced using the $\delta^{CS}(l)$ estimator in equation 4. Asterisks indicates 95% confidence interval (95% C.I.) does not contain zero.

Time relative to treatment	Dependent variable					
	Acre-feet withdrawn		Acres irrigated		Depth-applied	
	Estimate	95% C.I.	Estimate	95% C.I.	Estimate	95% C.I.
-23	-9.38	(-59.81, 41.04)	-0.41	(-13.37, 12.55)	-0.04	(-0.45, 0.38)
-22	-9.74	(-50.66, 31.18)	2.68	(-14.23, 19.59)	-0.11	(-0.43, 0.21)
-21	-8.41	(-37.12, 20.30)	2.53	(-4.71, 9.77)	-0.13	(-0.42, 0.16)
-20	-5.37	(-41.03, 30.29)	-11.1	(-42.31, 20.11)	0	(-0.22, 0.21)
-19	-10.05	(-33.01, 12.90)	-3.32	(-11.45, 4.82)	0	(-0.16, 0.15)
-18	0.58	(-20.07, 21.23)	-1.38	(-8.34, 5.58)	-0.02	(-0.16, 0.12)
-17	-1.07	(-21.01, 18.87)	-1.93	(-10.47, 6.60)	-0.01	(-0.14, 0.13)
-16	-0.92	(-19.28, 17.43)	3.86	(-6.63, 14.34)	-0.01	(-0.14, 0.11)
-15	5.74	(-16.43, 27.91)	-4.47	(-14.59, 5.64)	0.04	(-0.08, 0.16)
-14	-14.1	(-30.68, 2.48)	-2.1	(-14.09, 9.88)	-0.04	(-0.15, 0.07)
-13	-2.55	(-18.76, 13.67)	2.62	(-6.07, 11.31)	0.01	(-0.10, 0.12)
-12	-5.2	(-22.42, 12.02)	-1.41	(-10.83, 8.02)	-0.03	(-0.15, 0.09)
-11	0.02	(-14.98, 15.02)	1.13	(-7.18, 9.44)	0.02	(-0.08, 0.12)
-10	0.78	(-14.63, 16.20)	2.07	(-5.72, 9.86)	0	(-0.10, 0.09)
-9	0.94	(-12.05, 13.92)	-1.56	(-9.27, 6.15)	0.04	(-0.05, 0.12)
-8	2.22	(-10.62, 15.07)	-0.31	(-8.24, 7.62)	-0.01	(-0.09, 0.07)
-7	5.05	(-8.77, 18.86)	-2.48	(-9.55, 4.60)	0.03	(-0.04, 0.11)
-6	0.68	(-12.37, 13.73)	3.04	(-3.98, 10.06)	-0.03	(-0.10, 0.04)
-5	2.97	(-8.81, 14.75)	1.55	(-4.24, 7.34)	0.02	(-0.04, 0.08)
-4	0.25	(-10.91, 11.40)	-1.49	(-7.28, 4.29)	0.03	(-0.03, 0.09)
-3	2.38	(-7.27, 12.04)	1.02	(-3.87, 5.92)	-0.01	(-0.06, 0.05)
-2	-1.69	(-11.92, 8.55)	-1.98	(-6.89, 2.93)	0.01	(-0.05, 0.07)
-1	-3.06	(-12.64, 6.53)	0.63	(-4.04, 5.30)	-0.03	(-0.08, 0.03)
0	-18.95*	(-28.41, -9.49)	6.78*	(1.89, 11.68)	-0.15*	(-0.20, -0.10)
1	-9.79	(-20.18, 0.60)	9.03*	(2.73, 15.34)	-0.11*	(-0.17, -0.06)
2	-8.62	(-20.13, 2.89)	8.97*	(2.12, 15.81)	-0.09*	(-0.15, -0.04)
3	-4.6	(-16.02, 6.81)	10.83*	(3.90, 17.76)	-0.10*	(-0.16, -0.04)
4	-5.22	(-17.84, 7.41)	8.41*	(1.42, 15.41)	-0.10*	(-0.17, -0.04)
5	-8.51	(-21.89, 4.88)	9.65*	(1.44, 17.86)	-0.11*	(-0.18, -0.04)
6	-6.54	(-21.34, 8.25)	9.86*	(1.70, 18.01)	-0.09*	(-0.17, -0.02)
7	-5.39	(-21.21, 10.44)	11.11*	(2.31, 19.91)	-0.09*	(-0.17, -0.01)
8	-3.45	(-21.99, 15.09)	10.29*	(0.26, 20.32)	-0.06	(-0.15, 0.02)
9	1.72	(-16.91, 20.35)	13.42*	(1.07, 25.77)	-0.06	(-0.15, 0.03)
10	-3.7	(-25.63, 18.22)	12.58	(-0.46, 25.62)	-0.09	(-0.19, 0.00)
11	-0.03	(-24.62, 24.56)	12.05	(-3.23, 27.33)	-0.08	(-0.18, 0.03)
12	3.08	(-23.52, 29.68)	11.85	(-5.69, 29.38)	-0.05	(-0.17, 0.08)

Table C.6 (continued)

13	7.57	(-22.90, 38.04)	13.12	(-8.82, 35.05)	-0.04	(-0.17, 0.09)
14	4.5	(-30.25, 39.26)	9.24	(-16.79, 35.27)	-0.03	(-0.18, 0.11)
15	9.5	(-29.20, 48.19)	8.69	(-18.67, 36.05)	0	(-0.17, 0.17)
16	12.25	(-33.77, 58.26)	4.74	(-24.31, 33.78)	0.06	(-0.14, 0.27)
17	9.92	(-49.00, 68.83)	-1.86	(-40.58, 36.86)	0.07	(-0.15, 0.30)
18	24.95	(-32.93, 82.83)	-1.32	(-41.33, 38.69)	0.09	(-0.15, 0.32)
19	33.62	(-21.83, 89.07)	5.85	(-34.81, 46.51)	0.05	(-0.22, 0.33)
20	27.69	(-37.88, 93.25)	-0.74	(-43.41, 41.93)	0.06	(-0.21, 0.33)
21	40.98	(-26.58, 108.55)	2.83	(-44.20, 49.87)	0.17	(-0.13, 0.46)
22	17.41	(-48.62, 83.43)	14.09	(-30.41, 58.58)	0.01	(-0.40, 0.43)
23	33.19	(-21.72, 88.09)	28.87	(-16.42, 74.15)	0.03	(-0.49, 0.55)

Table C.7: Estimated dynamic treatment effects for the transition from traditional center pivot to LEPA irrigation produced using the $\delta^{CS}(l)$ estimator in equation 4. Asterisks indicates 95% confidence interval (95% C.I.) does not contain zero.

Time relative to treatment	Dependent variable					
	Acre-feet withdrawn		Acres irrigated		Depth-applied	
	Estimate	95% C.I.	Estimate	95% C.I.	Estimate	95% C.I.
-27	43.65	(-49.99, 137.29)	-40.48	(-198.49, 117.53)	0.48	(-1.41, 2.37)
-26	4.11	(-38.70, 46.91)	14.07	(-26.00, 54.14)	0.00	(-0.52, 0.52)
-25	7.55	(-24.51, 39.60)	-1.50	(-13.24, 10.24)	0.00	(-0.17, 0.17)
-24	-18.06	(-49.10, 12.97)	8.62	(-27.37, 44.60)	-0.22	(-0.64, 0.20)
-23	17.19	(-15.49, 49.87)	2.24	(-10.78, 15.25)	0.08	(-0.11, 0.26)
-22	6.78	(-38.82, 52.38)	-8.59	(-43.86, 26.68)	0.03	(-0.30, 0.36)
-21	-7.16	(-35.79, 21.47)	-7.34	(-19.04, 4.36)	0.01	(-0.12, 0.13)
-20	2.75	(-19.67, 25.17)	-0.64	(-12.66, 11.38)	0.04	(-0.07, 0.15)
-19	-6.76	(-23.58, 10.06)	-3.92	(-13.97, 6.12)	-0.04	(-0.13, 0.06)
-18	5.67	(-18.14, 29.48)	1.04	(-8.92, 11.00)	0.02	(-0.10, 0.13)
-17	-6.80	(-33.33, 19.73)	7.44	(-5.80, 20.69)	-0.05	(-0.18, 0.09)
-16	-3.98	(-45.42, 37.46)	-5.35	(-24.07, 13.38)	0.01	(-0.17, 0.19)
-15	-2.22	(-19.27, 14.83)	-2.84	(-11.49, 5.82)	-0.02	(-0.11, 0.07)
-14	-4.43	(-18.93, 10.07)	0.98	(-7.74, 9.70)	-0.03	(-0.11, 0.05)
-13	3.91	(-7.88, 15.71)	2.45	(-3.99, 8.89)	0.01	(-0.05, 0.08)
-12	-3.33	(-16.76, 10.11)	-2.92	(-9.29, 3.46)	0.00	(-0.06, 0.06)
-11	-3.17	(-13.85, 7.51)	0.14	(-5.32, 5.59)	-0.01	(-0.07, 0.05)
-10	-2.71	(-11.00, 5.58)	-2.29	(-7.09, 2.51)	-0.01	(-0.06, 0.04)
-9	1.22	(-6.77, 9.21)	2.23	(-1.99, 6.44)	-0.01	(-0.05, 0.04)
-8	-2.66	(-9.40, 4.08)	-2.07	(-5.49, 1.34)	0.00	(-0.04, 0.04)
-7	3.59	(-3.33, 10.51)	-0.62	(-4.08, 2.85)	0.01	(-0.02, 0.05)
-6	-5.23	(-10.50, 0.04)	0.62	(-1.96, 3.21)	-0.03	(-0.07, 0.00)
-5	-3.04	(-8.70, 2.63)	-0.20	(-2.91, 2.51)	0.00	(-0.03, 0.03)
-4	2.05	(-3.95, 8.05)	0.25	(-2.64, 3.14)	0.01	(-0.02, 0.04)
-3	3.07	(-2.90, 9.04)	0.71	(-1.92, 3.35)	0.01	(-0.02, 0.04)
-2	-2.10	(-7.87, 3.67)	-0.73	(-3.46, 1.99)	-0.01	(-0.03, 0.02)
-1	4.86	(-0.67, 10.39)	1.01	(-1.70, 3.73)	0.01	(-0.02, 0.04)
0	-0.66	(-5.58, 4.26)	-1.63	(-3.93, 0.67)	0.00	(-0.02, 0.03)
1	-1.44	(-7.16, 4.29)	-2.11	(-5.00, 0.77)	0.01	(-0.02, 0.04)
2	-1.27	(-7.78, 5.23)	-2.66	(-5.84, 0.53)	0.00	(-0.03, 0.03)
3	1.65	(-5.64, 8.95)	-0.67	(-4.00, 2.66)	0.00	(-0.03, 0.04)
4	1.09	(-7.71, 9.88)	-1.21	(-5.45, 3.02)	0.01	(-0.03, 0.05)
5	0.95	(-8.41, 10.31)	-0.86	(-5.64, 3.92)	0.01	(-0.03, 0.05)
6	-1.83	(-11.49, 7.84)	-1.62	(-6.96, 3.71)	0.00	(-0.04, 0.03)
7	-4.61	(-15.50, 6.28)	-2.36	(-8.40, 3.69)	-0.02	(-0.07, 0.02)
8	-4.62	(-16.53, 7.28)	-2.72	(-9.57, 4.13)	-0.02	(-0.06, 0.03)

Table C.7 (continued)

9	-6.40	(-20.41, 7.60)	-3.39	(-9.83, 3.05)	-0.01	(-0.06, 0.04)
10	-10.24	(-24.56, 4.08)	-3.98	(-11.68, 3.71)	-0.03	(-0.08, 0.03)
11	-11.01	(-25.30, 3.28)	-3.43	(-11.37, 4.52)	-0.03	(-0.09, 0.02)
12	-11.11	(-27.61, 5.39)	-2.21	(-11.06, 6.65)	-0.04	(-0.10, 0.02)
13	-12.23	(-30.59, 6.12)	-2.17	(-10.99, 6.65)	-0.03	(-0.11, 0.04)
14	-12.84	(-33.26, 7.59)	-2.48	(-12.73, 7.77)	-0.02	(-0.10, 0.06)
15	-7.63	(-29.08, 13.82)	-2.11	(-14.62, 10.41)	-0.01	(-0.10, 0.08)
16	-11.35	(-36.08, 13.38)	-2.39	(-15.51, 10.73)	-0.03	(-0.12, 0.06)
17	-11.19	(-37.85, 15.47)	-0.62	(-15.00, 13.77)	-0.05	(-0.14, 0.05)
18	-9.79	(-40.77, 21.19)	0.47	(-15.90, 16.84)	-0.04	(-0.14, 0.05)
19	-11.33	(-43.3, 20.64)	0.56	(-18.61, 19.73)	-0.06	(-0.18, 0.06)
20	-9.72	(-43.06, 23.61)	-2.02	(-21.72, 17.68)	-0.05	(-0.16, 0.07)
21	-17.65	(-57.95, 22.65)	-5.23	(-29.00, 18.53)	-0.08	(-0.21, 0.05)
22	-21.11	(-61.81, 19.58)	-6.98	(-30.10, 16.14)	-0.09	(-0.25, 0.07)
23	-24.69	(-54.95, 5.57)	-4.15	(-29.30, 20.99)	-0.13	(-0.30, 0.04)
24	-37.96*	(-68.83, -7.10)	-7.54	(-35.87, 20.78)	-0.22	(-0.45, 0.01)
25	-42.13*	(-80.63, -3.63)	-14.25	(-44.07, 15.58)	-0.24	(-0.49, 0.02)
26	-50.82*	(-93.91, -7.73)	-44.15	(-118.28, 29.98)	-0.23	(-0.63, 0.18)
27	-66.26*	(-119.51, -13.00)	-41.24	(-127.95, 45.48)	-0.33	(-1.00, 0.34)

Appendix D - Robustness checks

Table D.1: Results from parallel trends pre-test for the flood to center pivot sub-sample. *P*-values less than 0.10 indicate rejection of the null hypothesis that pre-treatment coefficients are jointly indistinguishable from zero at the 90% confidence level. Asterisks indicate time periods when the pre-test passes for all three dependent variables at the 90% level.

	Flood to center pivot Pre-test *P*-value		
Period tested	Acre-feet withdrawn	Acres irrigated	Depth-applied
1991 to 1995	0.89	0.07	0.08
1991 to 2000	0.03	0.09	0.01
1991 to 2005	0.00	0.07	0.00
1991 to 2010	0.00	0.00	0.00
1991 to 2015	0.00	0.00	0.00
1996 to 2000*	0.55	0.67	0.22
1996 to 2005*	0.11	0.73	0.27
1996 to 2010	0.00	0.04	0.16
1996 to 2015	0.00	0.00	0.00
2001 to 2005*	0.55	1.00	0.98
2001 to 2010	0.02	0.85	0.56
2001 to 2015	0.00	0.46	0.00
2006 to 2010*	0.18	0.33	0.64
2006 to 2015	0.03	0.55	0.01
2011 to 2015*	0.39	0.23	0.12

Table D.2: Results from parallel trends pre-test for the transition from traditional center pivot to LEPA. *P*-values less than 0.10 indicate rejection of the null hypothesis that pre-treatment coefficients are jointly indistinguishable from zero at the 90% confidence level. Asterisks indicate time periods when the pre-test passes for all three dependent variables at the 90% level.

	Traditional center pivot to LEPA Pre-test *P*-value		
Period tested	Acre-feet withdrawn	Acres irrigated	Depth-applied
1991 to 1995	0.00	0.76	0.01
1991 to 2000	0.00	0.71	0.00
1991 to 2005	0.00	0.52	0.00
1991 to 2010	0.00	0.00	0.00
1991 to 2015	0.00	0.52	0.00
1991 to 2019	0.00	0.10	0.00
1996 to 2000	0.55	0.30	0.06
1996 to 2005*	0.24	0.23	0.19
1996 to 2010	0.02	0.10	0.08
1996 to 2015	0.00	0.02	0.00
1996 to 2019	0.00	0.00	0.00
2001 to 2005*	0.23	0.26	0.45
2001 to 2010	0.06	0.65	0.28
2001 to 2015	0.00	0.80	0.00
2001 to 2019	0.00	0.26	0.00
2006 to 2010*	0.84	0.74	0.39
2006 to 2015	0.10	0.85	0.00
2006 to 2019	0.00	0.77	0.00
2011 to 2015	0.10	0.58	0.06
2011 to 2019	0.10	0.61	0.00
2016 to 2019*	0.17	0.54	0.67

Table D.3: Estimated average treatment effect of each technology change in levels for the δ^{CS} estimator (Callaway and Sant'Anna 2020) and TWFE using the time periods when the pre-test passes for each transition. Asterisks indicates 95% confidence interval does not contain zero.

Technology transition and years used	Estimator	Dependent variable		
		Acre-feet withdrawn	Acres irrigated	Depth-applied
Flood to center pivot (1996-2005)	Callaway and Sant'Anna (2020)	-9.88 (-22.83, 3.06)	10.38* (2.42, 18.34)	-0.12* (-0.19, -0.06)
	Two-way fixed effects	-16.93 (-23.94, -9.93)	5.54 (0.88, 10.20)	-0.14 (-0.18, -0.11)
Traditional center pivot to LEPA (1996-2005)	Callaway and Sant'Anna (2020)	0.90 (-5.89, 7.69)	-1.56 (-5.01, 1.88)	-0.00 (-0.03, 0.03)
	Two-way fixed effects	2.99 (-1.14, 6.13)	-0.43 (-1.85, 0.99)	0.01 (-0.01, 0.02)

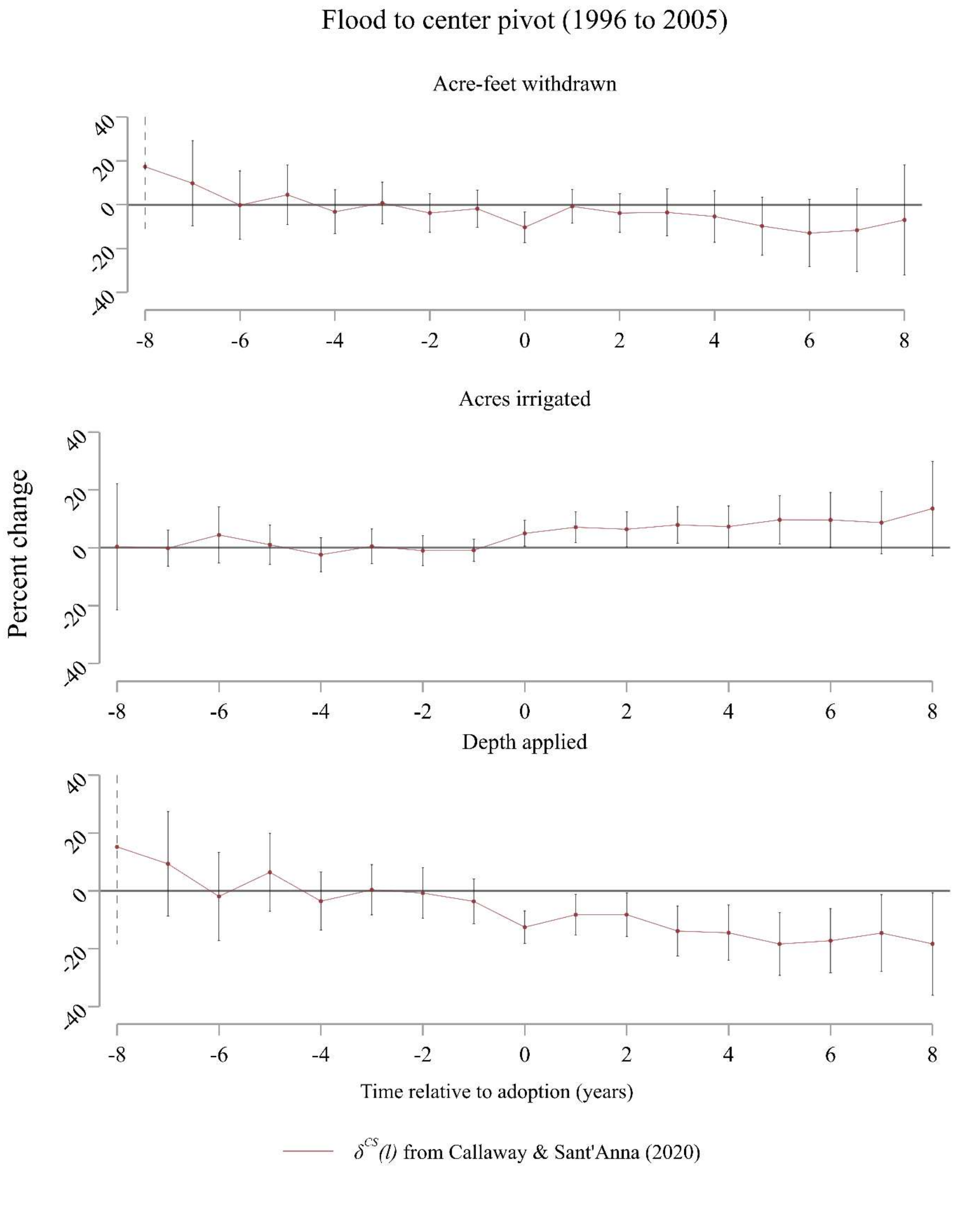

Figure D.1: Dynamic treatment effects due to converting from flood to center pivot irrigation for the time period when pre-test passes, 1996 to 2005. Effects are expressed as a percent change relative to the sample mean of each dependent variable. Error bars represent the 95% confidence interval, with dotted lines indicating the confidence interval extends beyond the y-axis range.

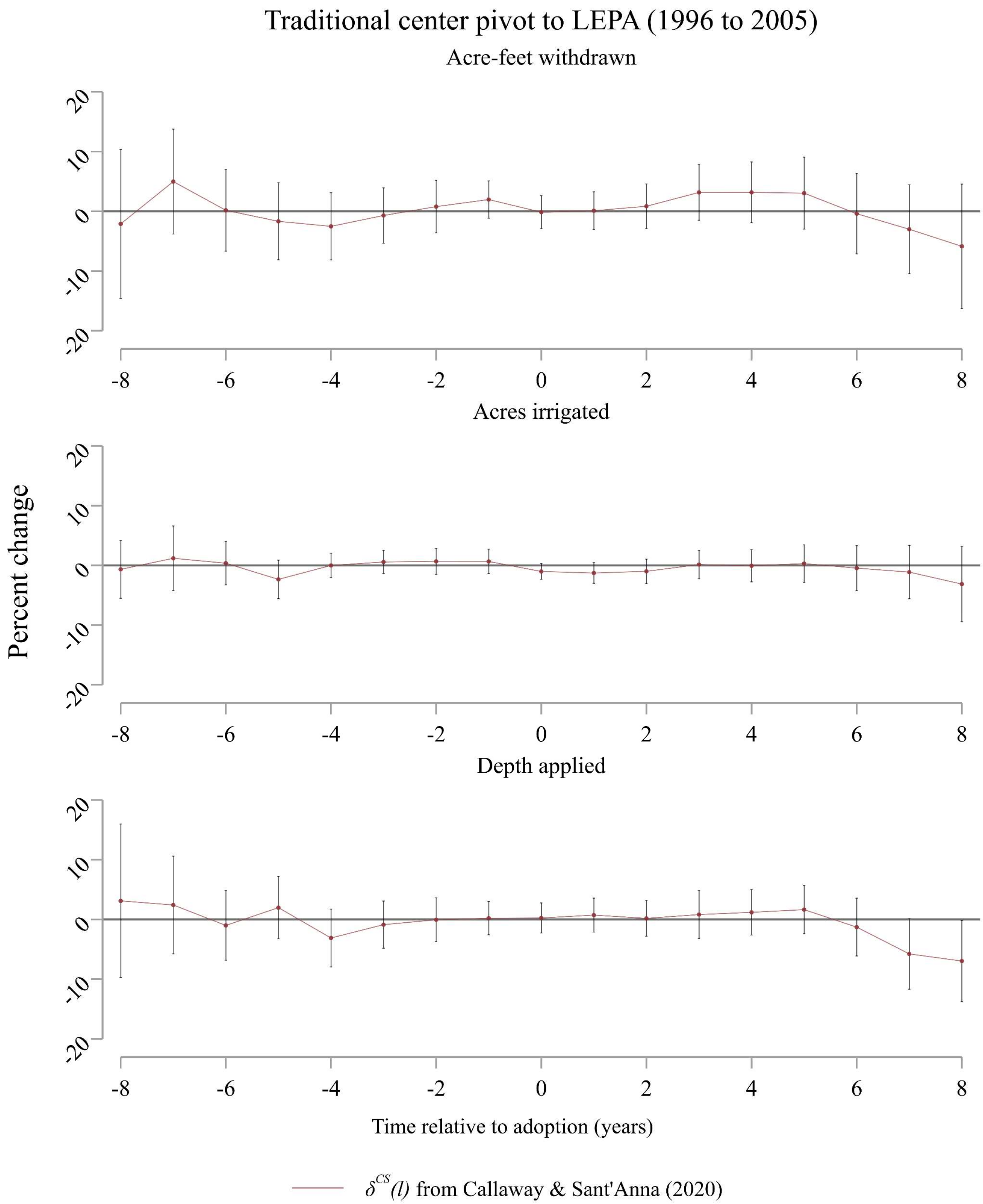

Figure D.2: Dynamic treatment effects due to switching from traditional center pivot to LEPA irrigation for the time period when pre-test passes, 1996 to 2005. Effects are expressed as a percent change relative to the sample mean of each dependent variable. Error bars represent the 95% confidence interval.

Table D.4: Balanced dynamic treatment effects for the effect of converting from flood to center pivot irrigation on acre-feet withdrawn. After balancing, the treated group only includes water right groups who are observed for the listed number of years after the change. Asterisks indicates 95% confidence interval does not contain zero.

Effect on groundwater withdrawals at l years relative to adoption	Balanced so treated water right groups adopted center pivot for at least t years			
	$t = 2$	$t = 4$	$t = 6$	$t = 8$
$l = -6$	-27.07 (-80.93, 26.79)			
$l = -5$	15.8 (-15.44, 47.04)			
$l = -4$	-6.03 (-27.21, 15.14)	-4.97 (-37.63, 27.68)		
$l = -3$	0.33 (-16.48, 17.15)	-7.75 (-26.6, 11.10)		
$l = -2$	-5.35 (-21.41, 10.70)	-4.36 (-24.79, 16.06)	-8.66 (-45.74, 28.42)	
$l = -1$	-3.18 (-17.39, 11.04)	-2.6 (-19.08, 13.89)	-3.70 (-27.18, 19.79)	
$l = 0$	-19.62* (-33.25, -6.00)	-19.75* (-33.84, -5.67)	-26.59* (-42.94, -10.23)	-38.52* (-67.65, -9.40)
$l = 1$	-1.85 (-16.96, 13.26)	-2.76 (-17.62, 12.09)	-4.59 (-25.39, 16.2)	-6.67* (-37.75, 24.42)
$l = 2$	-7.05 (-21.72, 7.61)	-11.89 (-27.77, 3.98)	-12.24 (-32.06, 7.57)	-32.5 (-61.7, -3.30)
$l = 3$		-11.47 (-28.53, 5.60)	-9.02 (-30.12, 12.07)	-17.41 * (-45.47, 10.65)
$l = 4$		-9.93 (-29.44, 9.59)	-17.68 (-41.19, 5.82)	-23.28 (-58.97, 12.42)
$l = 5$			-25.22 * (-50.21, -0.23)	-41.02 * (-79.36, -2.69)
$l = 6$			-23.94 (-49.96, 2.09)	-41.03 (-83.57, 1.51)
$l = 7$				-27.74 (-70.81, 15.32)
$l = 8$				-12.85 (-57.27, 31.57)

Table D.5: Balanced dynamic treatment effects for the effect of converting from flood to center pivot irrigation on acres irrigated. After balancing, the treated group only includes water right groups who are observed for the listed number of years after the change. Asterisks indicates 95% confidence interval does not contain zero.

Effect on irrigated acres at l years relative to adoption	Balanced so treated water right groups adopted center pivot for at least t years			
	$t = 2$	$t = 4$	$t = 6$	$t = 8$
$l = -6$	12.67 (-22.32, 47.67)			
$l = -5$	4.32 (-14.65, 23.29)			
$l = -4$	-5.99 (-18.91, 6.94)	-14.73 (-31.60, 2.13)		
$l = -3$	0.02 (-12.44, 12.48)	-2.49 (-19.29, 14.31)		
$l = -2$	-2.18 (-12.05, 7.69)	-2.49 (-13.91, 8.94)	-1.64 (-19.74, 16.46)	
$l = -1$	-2.05 (-9.09, 5.00)	-1.52 (-9.53, 6.48)	-4.01 (-15.39, 7.37)	
$l = 0$	10.8* (3.07, 18.52)	10.73* (2.42, 19.04)	12.39* (0.93, 23.86)	9.96 (-8.27, 28.19)
$l = 1$	12.19* (3.1, 21.27)	13.86* (5.40, 22.32)	17.78* (6.00, 29.55)	16.56 (-0.30, 33.43)
$l = 2$	10.7* (1.00, 20.40)	11.95* (1.96, 21.94)	15.19* (1.67, 28.70)	16.46 (-3.51, 36.43)
$l = 3$		13.63* (3.13, 24.14)	11.91 (-2.25, 26.07)	9.73 (-7.18, 26.64)
$l = 4$		12.2* (1.15, 23.26)	8.39 (-5.16, 21.94)	3.51 (-18.53, 25.54)
$l = 5$			13.35 (-0.16, 26.87)	12.43 (-5.87, 30.74)
$l = 6$			16.07* (1.15, 30.99)	16.48 (-3.55, 36.52)
$l = 7$				19.45 (-2.44, 41.33)
$l = 8$				22.59 (-1.93, 47.11)

Table D.6: Balanced dynamic treatment effects for the effect of converting from flood to center pivot irrigation on depth-applied. After balancing, the treated group only includes water right groups who are observed for the listed number of years after the change. Asterisks indicates 95% confidence interval does not contain zero.

Effect on depth-applied at l years relative to adoption	Balanced so treated water right groups adopted center pivot for at least t years			
	$t = 2$	$t = 4$	$t = 6$	$t = 8$
$l = -6$	-0.12 (-0.37, 0.13)			
$l = -5$	0.11 (-0.04, 0.27)			
$l = -4$	-0.03 (-0.16, 0.09)	0.00 (-0.19, 0.2)		
$l = -3$	0.00 (-0.11, 0.1)	-0.06 (-0.2, 0.09)		
$l = -2$	-0.01 (-0.09, 0.08)	-0.02 (-0.13, 0.09)	-0.02 (-0.21, 0.16)	
$l = -1$	-0.04 (-0.13, 0.04)	-0.02 (-0.11, 0.08)	-0.01 (-0.13, 0.11)	
$l = 0$	-0.15* (-0.22, -0.09)	-0.16* (-0.23, -0.09)	-0.2* (-0.28, -0.12)	-0.25* (-0.38, -0.12)
$l = 1$	-0.1* (-0.17, -0.02)	-0.11* (-0.19, -0.03)	-0.14* (-0.23, -0.05)	-0.16* (-0.3, -0.02)
$l = 2$	-0.09 * (-0.17, -0.01)	-0.13* (-0.22, -0.04)	-0.15* (-0.25, -0.05)	-0.26* (-0.41, -0.11)
$l = 3$		-0.18* (-0.28, -0.09)	-0.15* (-0.25, -0.06)	-0.2* (-0.36, -0.05)
$l = 4$		-0.16* (-0.25, -0.08)	-0.2* (-0.31, -0.09)	-0.26* (-0.44, -0.08)
$l = 5$			-0.23* (-0.34, -0.12)	-0.32* (-0.52, -0.12)
$l = 6$			-0.2* (-0.31, -0.08)	-0.31* (-0.48, -0.14)
$l = 7$			-0.02* (-0.21, 0.16	-0.23* (-0.42, -0.04)
$l = 8$				-0.21* (-0.4, -0.02)

Table D.7: Balanced dynamic treatment effects for the effect of changing from traditional center pivot to LEPA irrigation on acre-feet withdrawn. After balancing, the treated group only includes water right groups who are observed for the listed number of years after the change. Asterisks indicates 95% confidence interval does not contain zero.

Effect on groundwater withdrawals at l years relative to adoption	Balanced so treated water right groups adopted LEPA for at least t years			
	$t = 2$	$t = 4$	$t = 6$	$t = 8$
$l = -6$	0.86 (-21.94, 23.67)			
$l = -5$	-2.84 (-18.91, 13.23)			
$l = -4$	-5.91 (-17.65, 5.83)	-12.21 (-31.72, 7.31)		
$l = -3$	-1.83 (-11.04, 7.37)	-2.59 (-15.21, 10.03)		
$l = -2$	0.73 (-7.88, 9.35)	0.67 (-9.31, 10.65)	-4.38 (-23.9, 15.13)	
$l = -1$	4.52 (-1.95, 10.98)	4.56 (-2.46, 11.58)	4.69 (-4.99, 14.36)	
$l = 0$	0.16 (-5.29, 5.60)	1.20 (-4.2, 6.61)	-0.96 (-7.28, 5.37)	-2.64 (-11.54, 6.25)
$l = 1$	0.72 (-5.53, 6.97)	1.20 (-5.23, 7.63)	-2.15 (-9.76, 5.46)	-3.24 (-14.12, 7.65)
$l = 2$	1.69 (-5.34, 8.71)	3.21 (-4.36, 10.78)	-1.86 (-10.09, 6.37)	-10.16 (-20.35, 0.04)
$l = 3$		5.86 (-2.69, 14.41)	6.37 (-3.93, 16.67)	0.58 (-13.02, 14.19)
$l = 4$		6.37 (-3.84, 16.58)	8.99 (-2.94, 20.92)	3.86 (-11.44, 19.15)
$l = 5$			6.49 (-6, 18.97)	5.15 (-12.7, 22.99)
$l = 6$			-0.81 (-13.6, 11.99)	-2.5 (-18.1, 13.11)
$l = 7$				-11.05 (-28.79, 6.68)
$l = 8$				-11.77 (-31.47, 7.93)

Table D.8: Balanced dynamic treatment effects for the effect of changing from traditional center pivot to LEPA irrigation on acres irrigated. After balancing, the treated group only includes water right groups who are observed for the listed number of years after the change. Asterisks indicates 95% confidence interval does not contain zero.

Effect on acres irrigated at l years relative to adoption	Balanced so treated water right groups adopted LEPA for at least t years			
	$t = 2$	$t = 4$	$t = 6$	$t = 8$
$l = -6$	-1.72 (-14.54, 11.10)			
$l = -5$	-2.08 (-8.32, 4.16)			
$l = -4$	0.81 (-3.7, 5.32)	-2.72 (-8.75, 3.31)		
$l = -3$	0.16 (-3.52, 3.84)	1.39 (-3.3, 6.07)		
$l = -2$	1.26 (-2.71, 5.22)	2.21 (-2.39, 6.81)	5.53 (-3.18, 14.24)	
$l = -1$	1.42 (-1.96, 4.81)	0.98 (-2.8, 4.76)	0.75 (-4.04, 5.55)	
$l = 0$	-1.73 (-4.07, 0.60)	-1.36 (-3.79, 1.07)	-2.59 (-5.44, 0.26)	-3.5 (-7.45, 0.45)
$l = 1$	-2.08 (-5.23, 1.06)	-1.92 (-5.12, 1.27)	-2.91 (-6.64, 0.81)	-4.06 (-9.24, 1.12)
$l = 2$	-1.75 (-5.34, 1.84)	-1.01 (-4.65, 2.63)	-1.29 (-5.31, 2.73)	-4.51 (-9.85, 0.83)
$l = 3$		0.35 (-3.83, 4.53)	0.54 (-4.36, 5.45)	0.29 (-6.82, 7.39)
$l = 4$		-0.12 (-5.44, 5.19)	0.28 (-5.22, 5.77)	-0.33 (-7.26, 6.59)
$l = 5$			0.54 (-5.65, 6.72)	-1.81 (-10.33, 6.70)
$l = 6$			-0.8 (-7.41, 5.81)	-1.32 (-9.07, 6.44)
$l = 7$				-3.89 (-14.05, 6.28)
$l = 8$				-5.51 (-17.36, 6.34)

Table D.9: Balanced dynamic treatment effects for the effect of changing from traditional center pivot to LEPA irrigation on depth-applied. After balancing, the treated group only includes water right groups who are observed for the listed number of years after the change. Asterisks indicates 95% confidence interval does not contain zero.

Effect on depth-applied at l years relative to adoption	Balanced so treated water right groups adopted LEPA for at least t years			
	$t = 2$	$t = 4$	$t = 6$	$t = 8$
$l = -6$	-0.01 (-0.09, 0.07)			
$l = -5$	0.01 (-0.06, 0.08)			
$l = -4$	-0.04 (-0.1, 0.02)	-0.05 (-0.16, 0.06)		
$l = -3$	-0.01 (-0.05, 0.04)	-0.02 (-0.08, 0.04)		
$l = -2$	0.00 (-0.05, 0.04)	-0.01 (-0.06, 0.04)	-0.04 (-0.13, 0.04)	
$l = -1$	0.00 (-0.03, 0.04)	0 (-0.04, 0.04)	0.01 (-0.03, 0.06)	
$l = 0$	0.00 (-0.02, 0.03)	0.01 (-0.02, 0.03)	0.00 (-0.03, 0.03)	0.00 (-0.04, 0.05)
$l = 1$	0.01 (-0.02, 0.04)	0.01 (-0.02, 0.04)	-0.01 (-0.05, 0.03)	-0.01 (-0.06, 0.04)
$l = 2$	0.00 (-0.03, 0.04)	0.01 (-0.03, 0.04)	-0.03 (-0.06, 0.01)	-0.04 (-0.09, 0.01)
$l = 3$		0 (-0.03, 0.04)	0.00 (-0.05, 0.05)	-0.04 (-0.1, 0.02)
$l = 4$		0.01 (-0.03, 0.06)	0.02 (-0.03, 0.07)	-0.01 (-0.07, 0.06)
$l = 5$			0.02 (-0.04, 0.07)	0.02 (-0.05, 0.09)
$l = 6$			-0.01 (-0.07, 0.04)	-0.01 (-0.09, 0.06)
$l = 7$				-0.08* (-0.15, -0.01)
$l = 8$				-0.08 (-0.16, 0.00)

To test the robustness of our results, we also employ the DID_ℓ estimator from de Chaisemartin and D'Haultfoeuille (2022) to estimate the effect of adopting a new technology over all periods following adoption.[16] As in de Chaisemartin and D'Haultfoeuille (2022), we let $N^1_{t,\ell}$, indicate the number of irrigators in the group who first adopted the new technology ℓ years before t, and N^{nt}_t denote the number of irrigators in groups who have not adopted the technology from the beginning of the time series until t. Then, to estimate the average outcome across all post-treatment periods, and the dynamic treatment effects for each post-treatment period, we use the following difference-in-differences estimator from de Chaisemartin and D'Haultfoeuille (2022),

$$\widehat{DID}^X_{t,\ell} = \frac{1}{N^1_{t,\ell}} \sum_{\forall\, i \in\, g\, =\, t-\ell} \left(Y_{i,g,t} - Y_{i,g,t-\ell-1} - (X_{i,g,t} - X_{i,g,t-\ell-1})'\hat{\theta}_0\right) -$$

$$\frac{1}{N^{nt}_t} \sum_{g=t+1} \left[\sum_{i=1}^{N_{g,t}} \left(Y_{i,g,t} - Y_{i,g,t-\ell-1} - (X_{i,g,t} - X_{i,g,t-\ell-1})'\hat{\theta}_0\right)\right]. \qquad \text{(D.1)}$$

Equation D.1 compares the evolution of the outcome variable from $t - \ell - 1$ to t for those who adopted the new technology ℓ years ago with groups who have yet to adopt by t. Note, $g = T + 1$ for groups who never adopt the technology, so they are included in this second summation along with irrigators who adopt the technology in periods after t. This means the control group is comprised of both "not-yet-treated" and "never-treated" irrigators. Annual precipitation and evapotranspiration are accounted for in equation D.1 via an OLS regression of the outcome evolution within the control group, $\left(Y_{i,g,t} - Y_{i,g,t-\ell-1} \mid g > t\right)$, on the evolution of its time-varying covariates during the same period, $\left(X_{i,g,t} - X_{i,g,t-\ell-1} \mid g > t\right)$, and time fixed effects. Letting $\hat{\theta}_0$ indicate the estimated coefficients for $\left(X_{i,g,t} - X_{i,g,t-\ell-1}\right)$ from this

[16] The DID_ℓ estimator expands upon the DID_M estimator of instantaneous treatment effects outlined in de Chaisemartin and D'Haultfoeuille (2020).While the DID_ℓ estimator accommodates treatments that turn on and off over time, we limit our sample so the treatment group includes irrigators who switch into the new technology once and never revert to the older technology.

regression, the expressions within summations in equation D.1 subtract the change in outcomes we would expect given the treatment group's evolution of covariates from the observed outcome evolution to remove variation due to changes in the covariates.

The inclusion of covariates in the $DID_{t,\ell}^{X}$ estimator from equation D.1 requires the same conditional parallel trends assumption as two-way fixed effects regressions (Clement de Chaisemartin and D'Haultfoeuille 2020). Namely, the conditional common trends assumption requires that any differential trends in the outcome variable between groups are explained with a linear model in $X_{g,t} - X_{g,t-\ell-1}$, where the terms $X_{g,t}$ and $X_{g,t-\ell-1}$ contain the time-varying covariates for the reference groups in the period immediately prior to adoption, $t - \ell - 1$, and at time t.

Now, we turn our attention to aggregating the individual $DID_{t,\ell}^{X}$ estimates into an average effect for each length of treatment, ℓ, and the overall effect across all treatment durations. First, we construct a weighted average of $DID_{t,\ell}^{X}$ terms for each value of ℓ to generate event-study style estimates of the effect of using the new technology for ℓ years including the instantaneous treatment effect. To generate the weights, we define N_{ℓ}^{1} as the number of irrigators across all groups who are observed for at least ℓ years after adopting the new technology. Defining $\tilde{T}$ as the last period in which we observe an irrigator who still has not adopted the newer technology, we construct a weighted average of the effect of ℓ years using the new technology regardless of when the adoption decision was first made,

$$\widehat{DID}_{\ell}^{X} = \frac{1}{N_{\ell}^{1}} \sum_{t=\ell+2}^{\tilde{T}} N_{t,\ell}^{1} DID_{t,\ell}^{X}. \quad \text{(D.2)}$$

The weight for each $DID_{t,\ell}^{X}$ in equation D.2 is the number of irrigators in groups who adopted the technology ℓ years ago relative to period t, $N_{t,\ell}^{1}$, divided by the total number of irrigators who have a recorded outcome ℓ years after adopting the new technology, N_{ℓ}^{1}.

To recover the overall average treatment effect, we then take a weighted average of these $\hat{\delta}_{\ell}^{CD}$, or DID_{ℓ}^{X}, values across all values for ℓ. The weights are the number of irrigators in groups who are observed ℓ years after adoption divided by the total number of irrigators who adopt the technology at any point, $w_{\ell} = N_{\ell}^{1}/\sum_{\ell} N_{\ell}^{1}$. The overall average treatment effect can be expressed as:

$$\hat{\delta}^{CD} = \sum_{\forall \ell \geq 0} w_{\ell} DID_{\ell}^{X}, \tag{D.3}$$

where the CD superscript denotes that it is the de Chaisemartin and D'Haultfoeuille (2022) estimator.

There are four assumptions necessary for the individual $\widehat{DID}_{t,\ell}^{X}$ estimators to recover the effect of adopting the technology ℓ years before period t, and for the resulting aggregation, $\hat{\delta}^{CD}$, to be an unbiased estimator of the average treatment effect of adopting the new technology. First, the treatment design must be "sharp" so the sequence of treatment across all irrigators in a group is the same. We express this in the example within Appendix B by stating $D_{i,g,t} = D_{g,t}$. The second assumption, non-pathological design, requires there to be at least one cohort of irrigators who adopt the new technology at a time when another cohort continues to use the old technology. The first two assumptions are satisfied with our data.

The third assumption, that of no anticipation, requires there be no dependence between a group's untreated outcome and its future treatments. In our context, this means that we assume irrigators do not adjust their water use with the old technology in anticipation of adopting the more efficient technology. The fourth assumption requires the trajectories of the counterfactual, or never adopter, outcomes remain the same across all cohorts after accounting for the impact of covariates with a linear model in $X_{i,g,t} - X_{i,g,t-\ell-1}$. Using $Y_{i,g,t}(D_{T+1})$ to indicate the counterfactual outcome for groups with $g \leq T$, this assumption requires there to be a vector θ_0 so that within each group and time period cell, (g, t), the following does not change across groups for $t \geq 2$:

$$E\left[Y_{i,g,t}(D_{T+1}) - Y_{i,g,t-1}(D_{T+1}) - (X_{i,g,t} - X_{i,g,t-\ell-1})'\hat{\theta}_0 | D_{i,g,t}, X_{i,g,t}\right] \qquad \text{(D.5)}$$

Equation D.5 expresses a specific version of conditional parallel trends assumption, where groups can have differences in their counterfactual behavior if it is explained by the change in their covariates over time. This expression also requires the adoption behavior and counterfactual outcomes for different groups of irrigators to be independent, and that any random shocks affecting a group's never-treated outcome be mean independent of the group's treatment sequence. In our context, this allows water right group's counterfactual outcomes and treatment trajectories to differ so long as it is explained by the change in weather between time periods. However, we expect differential trends in water right groups' behavior due to heterogeneity in their time invariant characteristics, such as total irrigated acreage, to violate this assumption. As such, we create five sets of water right groups using quintiles of the groundwater withdrawn by water right groups in the first year they appear in each sub-sample dataset. We then use the non-parametric matching feature of de Chaisemartin et al.'s *did_multiplegt* STATA package to only compare outcomes within these quintiles when estimating $\hat{\delta}^{CD}$ for each of three technology changes (Clément de Chaisemartin, D'Haultfoeuille, and Guyonvarch 2019).

Given this specification, the $\hat{\delta}^{CD}$ estimator generates counterfactuals for adopters using the outcome evolution of all control observations in the same quintile of initial withdrawals conditional on the evolution of time-varying covariates. If differences between the counterfactual outcomes of adopters and control water right groups can be explained by a linear function of time-varying covariates—precipitation and evapotranspiration in our context—then the conditional parallel trends assumption for the $\hat{\delta}^{CD}$ estimator may be more likely to hold. However, the $\hat{\delta}^{CD}$ estimator may end up using water right groups who are dissimilar to treated groups as controls because they share similar time-varying covariate behavior as the treated units.

Table D.10: Estimated average treatment effect for each technology change across all three estimators and dependent variables using the full time periods for each sub-sample. Asterisks indicates 95% confidence interval does not contain zero.

Technology transition	Estimator	Dependent variable		
		Acre-feet withdrawn	Acres irrigated	Depth-applied
Flood to center pivot	Callaway and Sant'Anna (2020)	2.79 (-14.66, 20.23)	10.31 (-0.55, 21.16)	-0.06 (-0.14, 0.03)
	de Chaisemartin & D'Haultfouille (2021)	5.58 (-5.76, 16.92)	12.10* (5.74, 18.45)	-0.04 (0.01, -0.10)
	TWFE	-17.90* (-22.86, -12.95)	6.47* (2.99, 9.95)	-0.14* (-0.17, -0.12)
Traditional center pivot to LEPA	Callaway and Sant'Anna (2020)	-6.78 (-17.29, 3.72)	-2.07 (-8.58, 4.44)	-0.02 (-0.06, 0.02)
	de Chaisemartin & D'Haultfouille (2021)	0.06 (-2.47, 2.03)	-0.22 (-2.47, 2.03)	0.00 (-0.03, 0.02)
	TWFE	5.91* (3.33, 8.5)	-0.47 (-1.82, 0.87)	0.03* (0.02, 0.04)

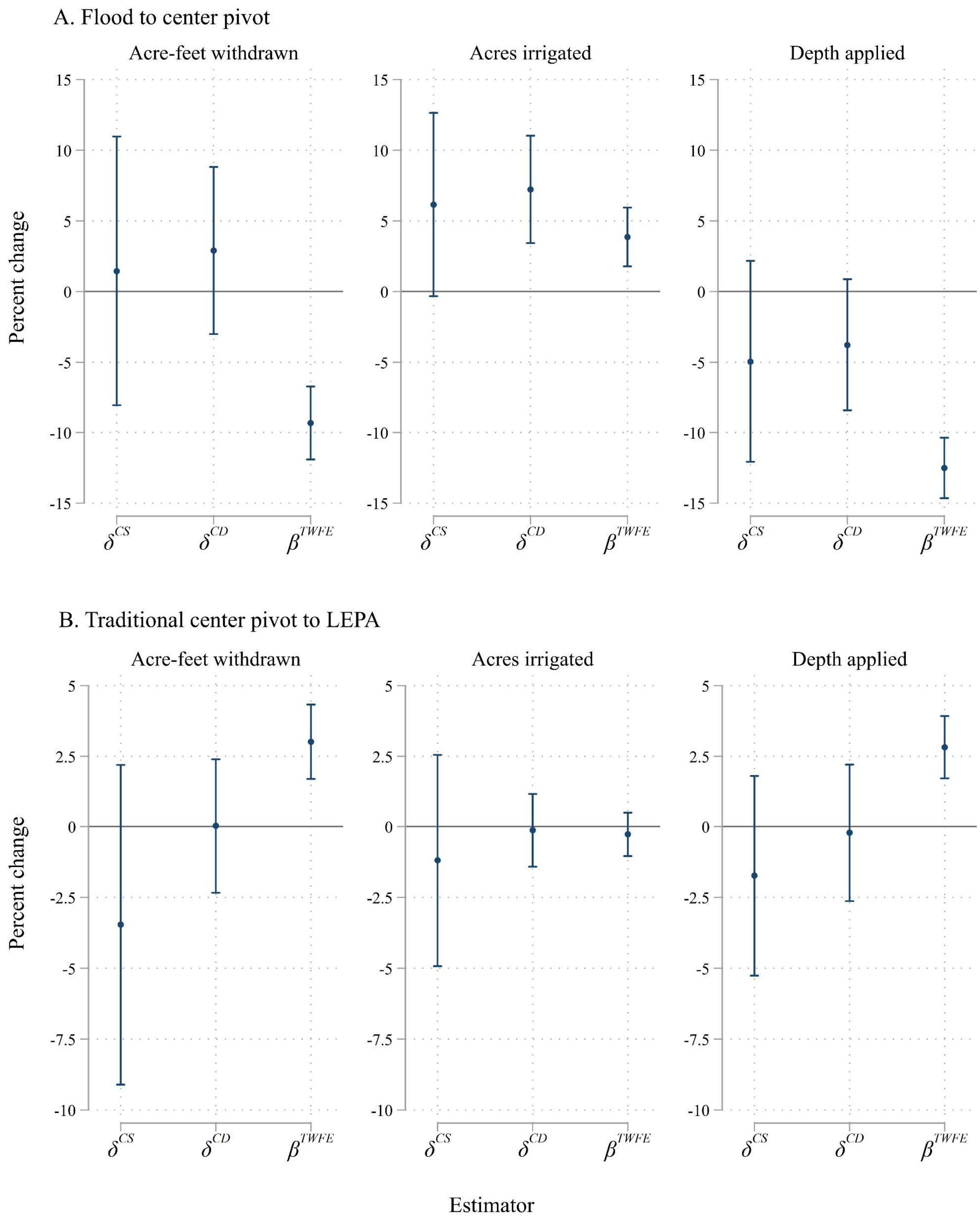

Figure D.3: Comparison of average treatment effect estimates for the preferred δ^{CS} estimator from Callaway and Sant'Anna (2020), the δ^{CD} estimator from de Chaisemartin and D'Haultfoeuille (2022) described in Appendix D, and two-way fixed effects (TWFE) estimation. Treatment effects are expressed as a percent change relative to the sample mean of each dependent variable.

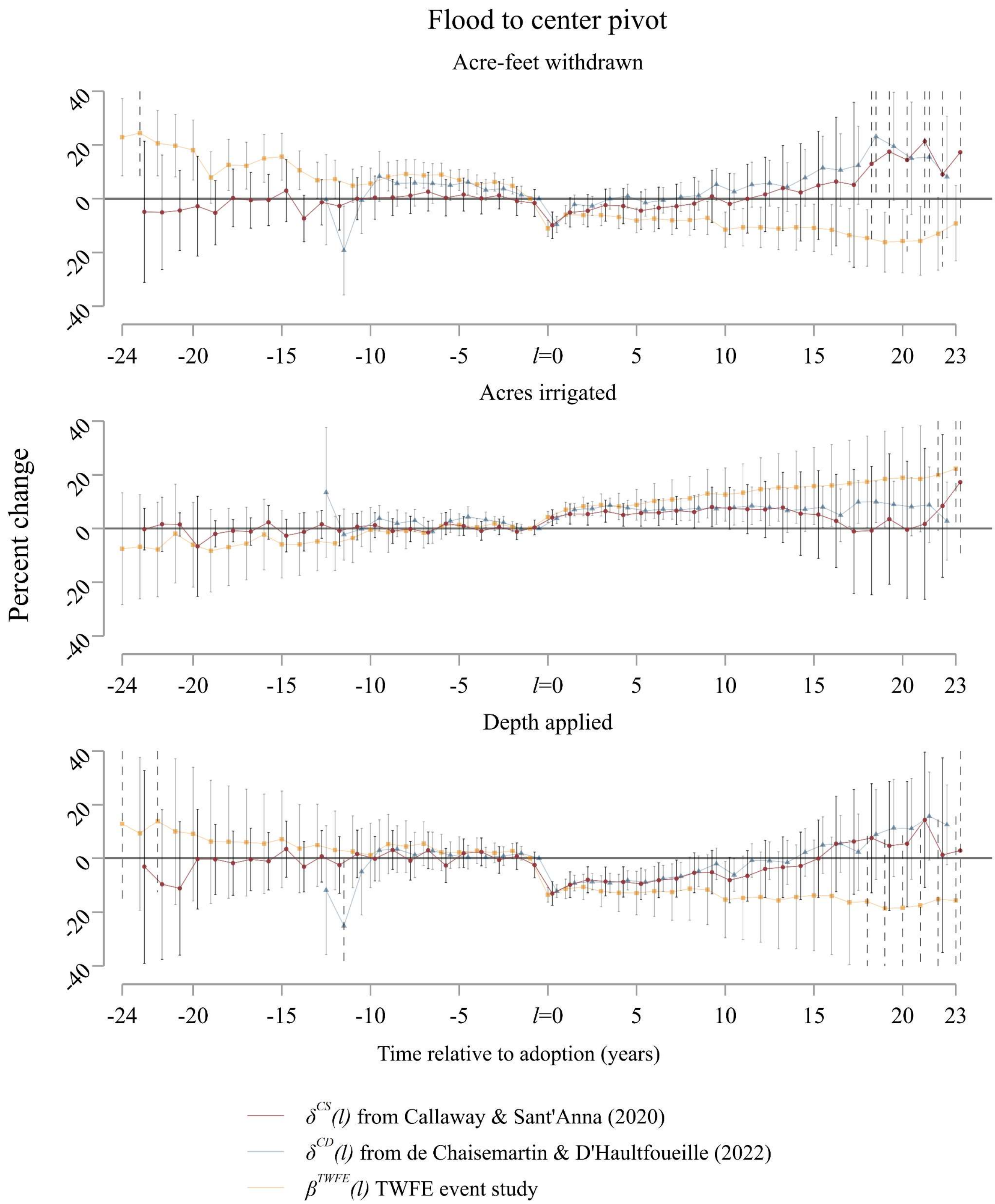

Figure D.4: Effect of changing from flood to center pivot irrigation at time l, where l is years relative to when center pivot is first adopted. Effects are expressed as a percent change relative to the sample mean of each dependent variable. Error bars represent the 95% confidence interval, with dotted lines indicating the confidence interval extends beyond the y-axis range.

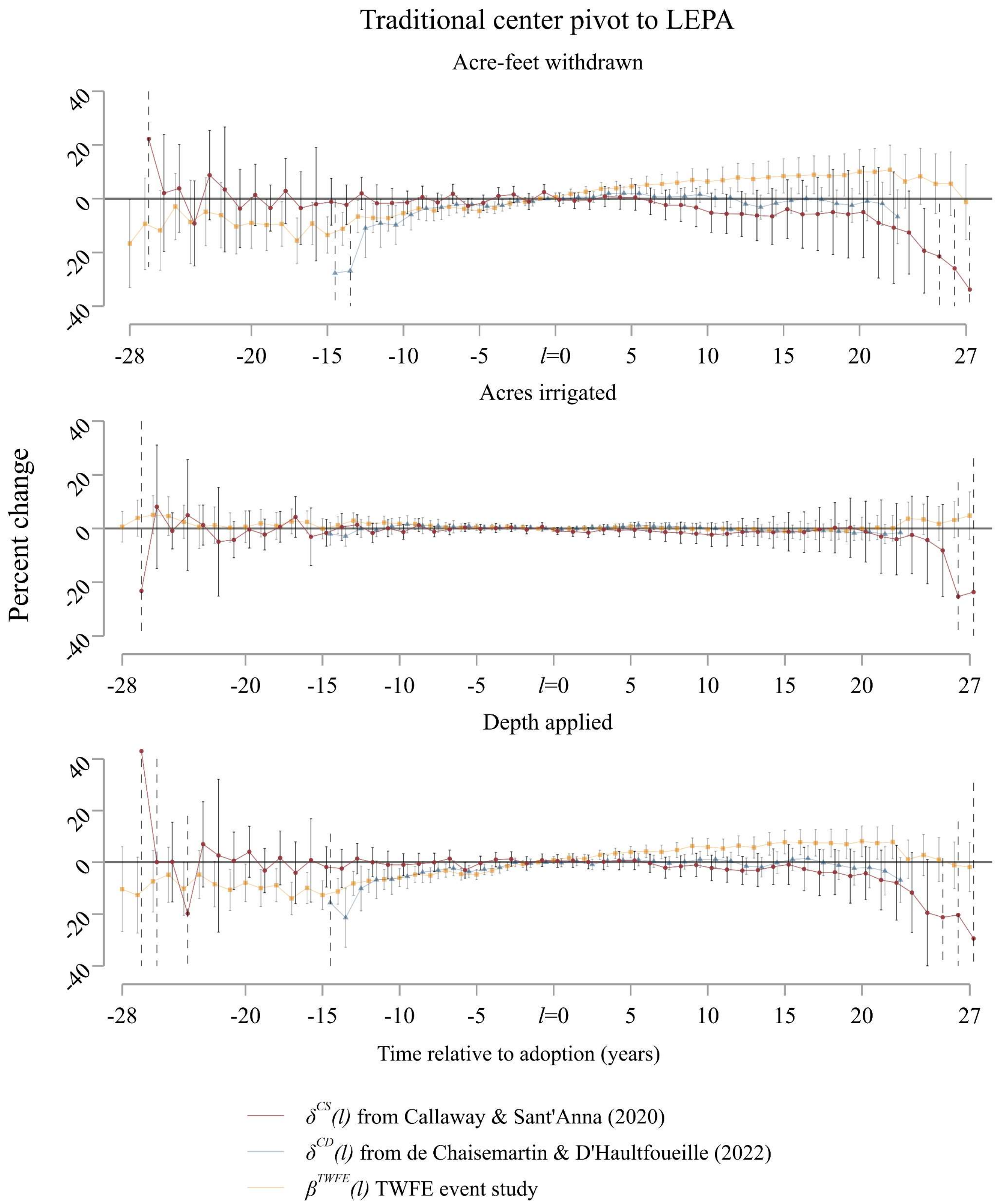

Figure D.5 Effect of changing from traditional center pivot to LEPA irrigation at time l, where l is years relative to when LEPA is first adopted. Effects are expressed as a percent change relative to the sample mean of each dependent variable. Error bars represent the 95% confidence interval, with dotted lines indicating the confidence interval extends beyond the y-axis range.