Quantifying the impact of water policy: measuring adaptations of a stakeholder-led irrigation water management plan in kansas using difference-in-differences

by

Krystal Drysdale

B.S., Missouri State University, 2007
M.N.A.S., Missouri State University, 2011
M.S., Kansas State University, 2015

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2020

Abstract

The goal of this research is to identify the effects of a local collective action management plan on irrigators in Kansas. I compare changes in water use decisions of irrigators located inside the policy boundary to changes in water use decisions of irrigators located within a five mile buffer surrounding the Sheridan County 6 Local Enhanced Management Area (LEMA). I use a Difference-in-Difference regression model to estimate the effects of the LEMA on irrigated acreage, irrigation intensity, and crop type to uncover the adaptation strategies adopted by farmers. I also estimate how the LEMA impacted crop yields and the use of agricultural inputs such as herbicides, pesticides, fertilizer, and seed. The key assumption for the empirical model is that irrigation decisions inside the LEMA boundary would have followed the same trend as those in the 5 mile boundary if the LEMA water use restriction had not been in place.

The change in total water use is decomposed into three adjustments: changes in irrigated acreage (extensive margin), changes in applied water intensity on the same crop (direct intensive margin), and changes in crop allocations (indirect intensive margin). My results indicate that the LEMA caused a reduction in total water use of 25%. The total change in water use was due to a 4% reduction at the extensive margin, 19% at the direct intensive margin and 3% at the indirect intensive margin. The LEMA resulted in an 8% reduction in corn yield and a 4% reduction to soybean yield, the primary crops in the region. I further estimate that the changes in cropping patterns due

to changes at the extensive margin result in a 15% reduction in agricultural input expenditures through changes in cropping patterns.

This study improves our understanding of the effects of this type of policy and provides implications for future water policy management initiatives. Global considerations of depleted groundwater resources have become of greater concern and initiatives such as the Sheridan County 6 LEMA could offer alternative strategies for effective resource management through a collective action management plan led by farmers and legally enforceable by the state.

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Major Professor
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Dedication

I would like to dedicate this work to my twin boys, Dominic and Jayden. You are the reason I returned to school when you were 2 years old to begin my Master's program so that I could make sure that I practiced what I preach. I wanted to give you everything. I knew if I was going to instill in you what it means to be dedicated and persevere I had to call on myself to show up in every way both for you as a mother as well as myself. That meant many sleepless nights not only caring for the two of you as a single parent, but sleepless nights in front of a computer pursuing my own personal dreams and desires.

You have been the most amazing inspiration for me on this journey and let me drag you across the country so that I could begin a new career. I could not have been blessed with any more remarkable young men. You both have watched me over the last 10 years as I made my way through my graduate school adventure. Whether it was our summer at the Mississippi beach house catching our own crabs and taking late night walks on the beach, or racing snails and making igloos in our tiny backyard in Kansas, to our impromptu talks about the universe and aliens in Arizona. I am so grateful that you both were so patient with me and made it incredibly rewarding and joyful.

Love you – Love You More – Impossible

Chapter 1 - Introduction

1.1 US Groundwater Policy Management

Depleting groundwater resources has become a crucial topic across the US. The High Plains Aquifer is the largest groundwater storage reservoir in the US covering 174,000 square miles (110 million acres) of the Great Plains stretching across eight states including Colorado, Kansas, Nebraska, New Mexico, Oklahoma, South Dakota, Texas, and Wyoming (McGuire, 2002) (Figure 1).

According to the US Department of the Interior, the future of secure water supplies is impacted by increasing competing demands from population growth, agriculture, development and climate change. This drives the necessity for states and local communities to provide leadership and enactment of policies to increase water resources, restore watersheds and invest in programs and management strategies that contribute to reversing the growing water crises across the US. Defining specific water policy directives for water quality or quantity issues can be difficult, however, with various stakeholders having opposing points of interest.

Over time increased groundwater pumping from various uses has resulted in substantial water table declines across the aquifer. Although irrigated agriculture is fed from both surface and groundwater, the over-exploitation of the aquifer's resources could significantly change the landscape of crop production in the US. Sixty percent of US irrigated land relies directly on groundwater pumping and irrigated land over the High Plains account for roughly 27%, making it the largest irrigation-sustained cropland in the world. (USGS, 2013).

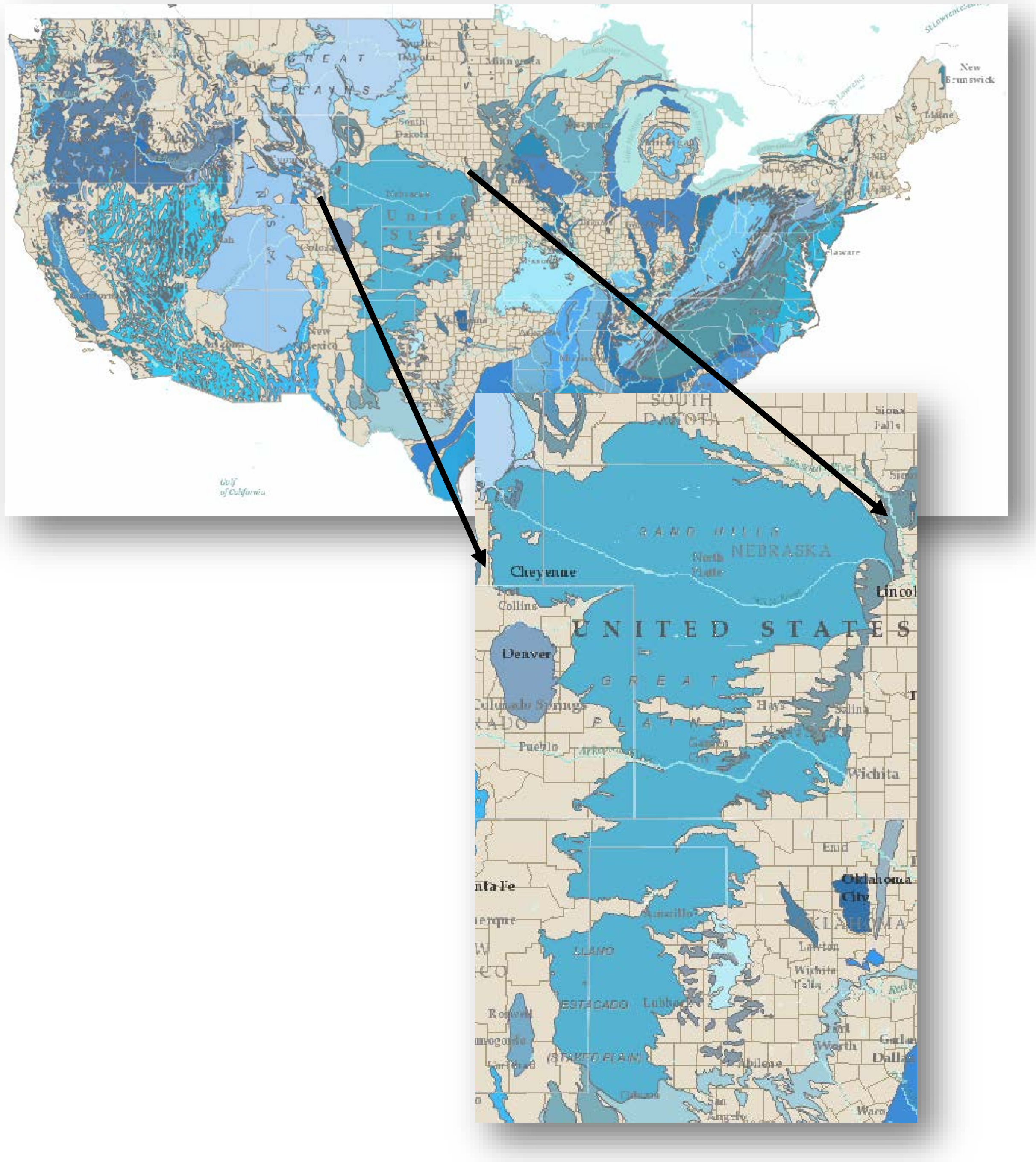


Figure 1: Map of the High Plains Aquifer

Concerns about depleted aquifers for agricultural production are not unique to the Great Plains. Groundwater extraction for irrigation provides a substantial increase in crop yields and stabilizes profits due to uncertain weather; however, using data from NASA's GRACE satellite, Famiglietti (2014) found that groundwater is being depleted in the largest global agricultural zones that could decrease crop production and subsequently raise food prices. In response to the growing concern over appropriate management of the aquifer farmers in Sheridan County, Kansas helped to form a Local Enhanced Management Area (LEMA) in an effort to self-regulate their water use (Figure 2).

Ostrom (2009) described factors that lead to collective action indicating that users of a resource will invest their time and energy and self-organize to avert a tragedy of the commons when it becomes profitable to do so. This occurs when benefits exceed the perceived costs of regulation. Although joint benefits may be established between users, self-organizing to sustain a resource increases time burdens for the users and could result in a loss of short-term economic gains causing users to avoid these costly changes and continue to overuse the resource. Farmers may be more likely to pursue these collective action efforts to the extent that they can adapt to water restrictions and offset the short-run negative impacts. The results from this study give some insights into the adaptation strategies pursued by farmers.

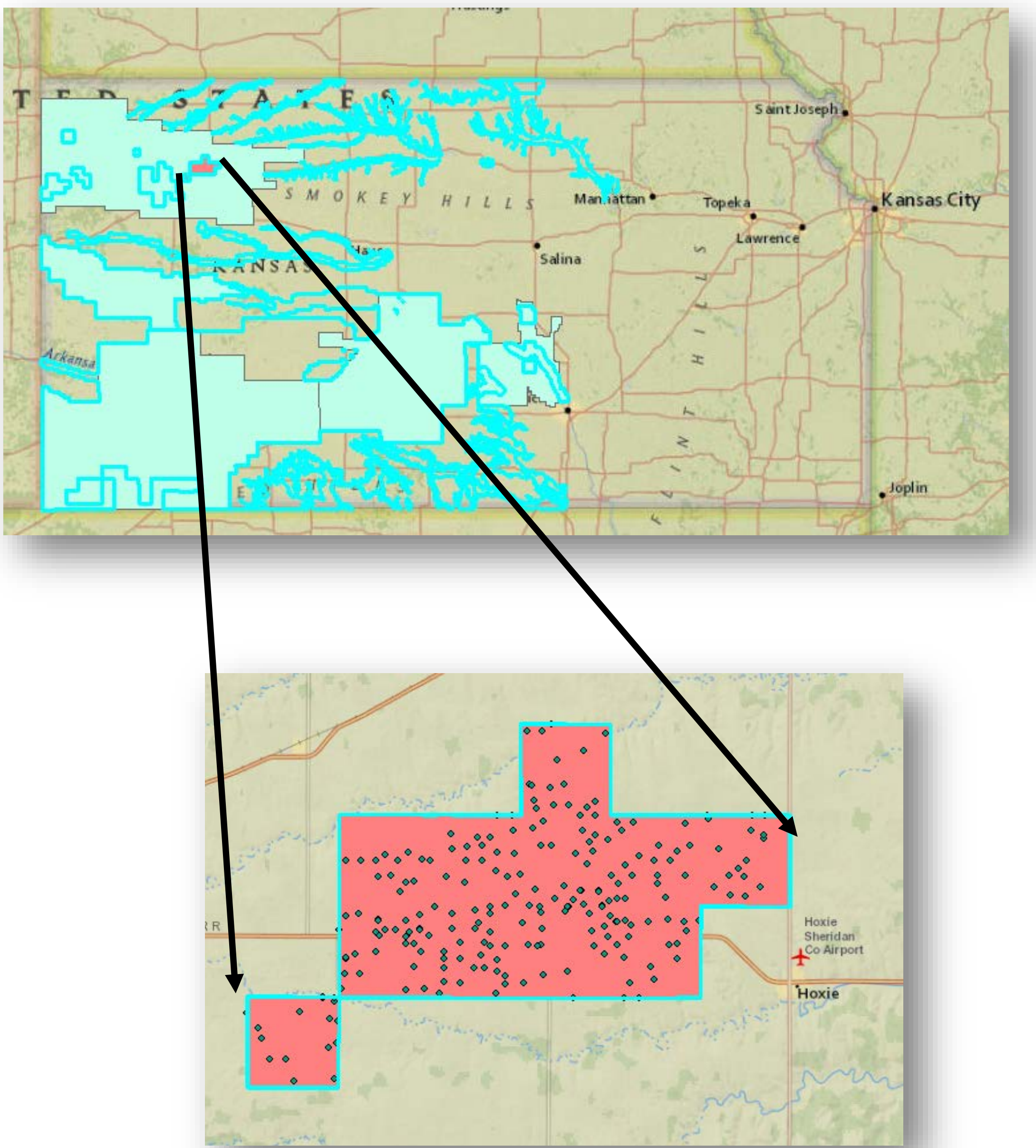


Figure 2: Map of Sheridan 6 Local Enhanced Management Area LEMA

1.2 Background on the Sheridan 6 LEMA

In 2012, new legislation granted Kansas Groundwater Management Districts (GMDs) the power to originate their own localized water conservation management plans which are then legally enforced by the state). Farmers in Sheridan County, located in the northwestern corner of Kansas participated in the process to impose restrictions on themselves by forming a Local Enhanced Management Area (LEMA) in 2013 as a collective action effort to regulate their water use.

As described by the order of the Chief Engineer, the overarching goal of the LEMA is a collective action to restrict irrigated groundwater rights to no more than 114,000 acre-feet total over January 1, 2013, and December 31, 2017, in a manner that preserves the economic benefits of irrigation further into the future. The 99 square mile area maintains 185 wells for irrigation and 10 non-irrigation wells and puts in place the goal of reducing groundwater pumping by approximately 20% whereby restricting irrigators to a five-year allocation of 55 inches/acre each (KDA, 2013).

In July of 2012, the Sheridan 6 LEMA proposal was transmitted to the Division of Water Resources (DWR) including the legal descriptions of sections to be included in the LEMA and goals and management actions for limiting water use. The proposal was generated through a public consensus process undertaken by the stakeholders of the SD-6 High Priority Area over the course of eleven noticed meetings and two subcommittee meetings beginning in 2008. The proposed LEMA including all wells located in the high priority area, not just wells of irrigators who may have been in favor of the water policy. Although the LEMA was in part farmer-led, the resulting defined boundary was formally decided externally, by the SD-6 advisory board that consisted of not only residents, owners, and operators but also representatives from the Division of Water Resources, Kansas Department of Agriculture, and Groundwater Management District 4. The notes from the June 17, 2009 meeting outlined exactly how the boundary was defined as follows:

> *The observation wells were used to generate an interpolated water level value for the center of every section. The 1997 section-center values were subtracted from the 2006 values and any section that declined 9% or more was identified. The reported water use was also aggregated for every section and any section that had more than 275 acre feet of annually reported water use was identified. Next, any ¼ Township that had two or more identified sections, was designated as a High Priority Area ¼ Township. Finally, the ¼ Townships were combined to form the 6 High Priority Areas.*

Many farmers who spoke out in support of the LEMA indicated that they felt that the LEMA provided enough flexibility in water allocation from year to year such that farmers would capitalize on their abilities to adapt and could actually be more profitable allowing future generations to continue irrigation practices. It is noted when questioned about how the irrigators felt the water restriction might impact their profits in one of the policy planning meetings, one farmer replied, “We’ll probably net more (profits)...”. This did not come without criticisms; however, with other farmers pointing out possible disproportionate water use based on unequal water right allocations between farmers within the restricted boundaries and a possible result of increased water use due to unlimited flexibility of allocation between water rights and unlimited well locations. Some argued this gives farmers the ability to purchase additional water rights to irrigate their present place of use causing potential for more water use than before the LEMA (KDA, 2013).

The water management plan is of interest to many due to its uncommon collective action establishment with direct input from the irrigators who have an interest in extending the life of the aquifer. The boundaries contained within the LEMA are defined by critical groundwater conditions and discussions about new LEMA enactment are currently being initiated in GMDs across the state. This includes GMD 4 in its entirety, five west-central counties (GMD 1), and 12 south-west counties (GMD 3) suggesting more farmers will be under these quantity restrictive policies in the near future. The term LEMA generally refers to this type of water management plan, however, in this paper, the term will subsequently describe the original Sheridan 6 LEMA as it is the focus of this analysis.

The Kansas Geological survey maintains and continuously monitors index wells in the three western Kansas GMDs to monitor the High Plains aquifer. Although it is unclear exactly how much time it takes for water savings to modify the depth to water of the aquifer, the recent study by Deines et al. (2019) found evidence of stabilizing groundwater levels inside the LEMA compared to outside the LEMA.

1.3 Research Overview

The concentration of this research is to consider impacts from the collective action water quantity restriction policy implemented in Sheridan County, Kansas. We use Difference-in-Difference estimators to compare changes in irrigation behavior inside the policy boundary to behavior in a 5-mile buffer zone outside the policy boundary. I estimate the effect of the policy on total water use, irrigated acreage, water intensity, cropping patterns and yields. The results give new insights into how irrigators adjusted their behavior to adapt to the restriction in the short run. By understanding the different margins of adjustment the results also indicate the potential effect of water restrictions on other agribusiness industries due to changes in agricultural outputs and inputs. I also wanted to consider possible unintended consequences from the water management plan and address the concerns of the irrigators proposed in the planning process related to disproportionate water restrictions.

Additionally, it is important to note that the Difference-in-Differences framework has strict underlying assumptions. It controls for unobserved heterogeneity that is constant over time and correlated with the dependent variables such that by differencing the data I can remove these time-invariant portions of the model. Additionally, it controls for unobserved heterogeneity that is constant across individuals and parsed out by a second differencing in the data. However, I believe there exists additional variation among farmers that cannot be completely captured by the D-I-D model such that I propose an additional secondary fixed effects regression model that controls for differential changes over time by farmer.

This analysis outlines the methodology for estimating the effects of the policy on the LEMA irrigators by beginning with the literature review in Chapter 2 which covers Groundwater Policy and Management in the US, previous studies of water demand management and decomposed marginal estimates and elasticities as well as yield estimation from simulation models and regional specific water budgets. I then outline in Chapter 3 the conceptual model of irrigator water use decisions before presenting the data, variables, and model controls in Chapter 4 in addition to an explanation of the defined boundary areas. For the purposes of establishing our model, it is important to note how the boundary of the LEMA group was defined. Chapter 5 explains the fundamentals of the D-I-D model empirical methods including the specification of my preferred model, the methodology for decomposing marginal effects of water use and specified production function. This chapter includes further validation of the methods with explanations of the policy event study, dummy corrections, fit of production function and use of robust standard errors. Finally, Chapters 6,7, and 8 cover the results for extensive and intensive marginal changes in water use, changes in cropping patterns and input expenditures, and changes in crop yields, respectively.

Chapter 2 - Literature Review

Previous studies that address water demand analysis are broad and include topics of water pricing, crop production and groundwater sustainability which provide valuable background for this study. I begin with a discussion of the general issue of long-term groundwater management as it applies to the study area to establish the timeliness and need for this research. I then narrow the focus to the literature that specifically discusses water user response to price and various demand shifters to introduce the void that our estimation of the direct effect from a water quantity restriction will fill. Finally, because this study uses an estimation approach that is based on a strict set of underlying assumptions I also include a section of literature that addresses potential shortcomings and current studies that outline improvements to the estimation methodology.

2.1 Groundwater Policy and Management

The issue of appropriate water use management strategies is not just isolated to the Ogallala Aquifer. A common theme within all water policy literature is uncertainty toward future climate and groundwater depletion rates as agriculture becomes increasingly dependent on irrigation technologies. This concern has been long withstanding with studies beginning in the early 1970s attempting to evaluate which types of policy-induced welfare maximization. In particular, the study by Mapp and Eidman (1976) considered a quantity limitation and a graduated tax to determine the optimal policy instrument in the central basin of the Ogallala Aquifer. While the quantity restriction might be preferable to policy makers due to its ability to reduce water-use rates by the largest amount and easier to implement, they found that it provided the lowest level of net farm income with the greatest relative variability. Historically, many irrigators share these sentiments and have tended to be against water restrictive policies.

An early study modeling regulated pumping costs in the Texas High Plains indicated that even in the face of decreased groundwater resources, the costs for regulating Texas farmers were too high and concluded that no regulations of groundwater withdrawals needed to be taken (Nieswiadomy, 1985). This determination was based on the previous study by Gisser and Sanchez (1980) who established the Gisser-Sanchez rule. This widely controversial paradox suggests that economic benefits from regulating irrigated groundwater use for irrigation are negligible if the groundwater storage capacity is relatively large and the demand for groundwater is highly inelastic. At the time, further examination of the rule in other western states was not plausible due to a lack of farm-level data on irrigated users. Furthermore, current studies lend evidence to the contrary indicating structured policy regulations are necessary for improved groundwater management.

In particular, the study by Kim et al. (2015) concluded that the Gisser-Sanchez rule is not applicable when irrigation technology is allowed to vary across time. Rather than leaving this resource to the tragedy of the commons, the research constructs a theoretical justification for developing socially optimal rates of groundwater extraction and conclude that there may be considerable scope for improving groundwater management, including increased groundwater quantity restrictions. Additionally, another recent study by Peterson and Ding (2005) presented a dynamic model of Kansas and Colorado examining the expected effects of alternative restriction policy scenarios. The research determined that without water policy intervention, the saturated thickness of the Ogallala would be reduced by more than 50 percent, and most irrigated cropland would revert back to rain-fed cropland within 60 years. Furthermore, at the time of his study, Neiswiadomy had projected the life of the aquifer beneath the Texas High Plains to have another 40-50 years before the steady-state solution was reached. This seems short-sighted given that 30 years later have passed and the condition of the aquifer continues to still be a topic of great concern and research with many stakeholders interested in determining sustainable appropriation of the groundwater such that the aquifer continues to be a viable resource for future generations.

Many times, the focus of water policy is on improvements in water-saving technology; however, the study by Peterson and Ding (2005) indicate that these policies may have adverse effects such that improvements in irrigation efficiency could potentially increase total irrigated acres (i.e. whereby increasing total water consumption) and is dependent on relationships in the crop production process. A more recent study by Pfeiffer and Lin (2014) uses empirical evidence in western Kansas to validate Peterson and Ding's findings, concluding that on average, the adoption of more efficient irrigation technology resulted in increased water use from changes in crop type. As a result, a need for more empirical evidence at the farm level is necessary to model irrigation strategy choice behavior that includes variables relating to weather, crop and soil characteristics.

Hornbeck and Keskin (2014) studied how agricultural production decisions changed from the introduction of irrigation over the Ogallala Aquifer. They considered impacts from drought and concluded irrigated land use adjusted toward water-intensive crops, whereas, irrigators in nearby water-scarce areas maintained lower value drought-resistant cropping patterns that naturally reduce water quantity sensitivity. While the study presented by Peterson and Ding (2005) provides a scenario framework for the consideration of water restrictive policies, the current empirical studies on water policy effects neglect to evaluate irrigated user's decisions from a water use restriction with the exception of Hornbeck and Keskin (2014) who quantified effects by comparing counties over the Ogallala with nearby similar counties while controlling for average differences in soil characteristics and weather. Smith et al. (2017) used a Difference-in-Differences model and found that a self-imposed groundwater pumping fee in Colorado was effective at reducing water use. Additionally, a study by Deines et. al. (2019) evaluated the marginal effects on irrigators inside the Sheridan 6 Local Enhanced Management Area (LEMA) using a Bayesian structural time series approach. This approach uses a counterfactual control group as the basis for comparison to identify the causal effect of the policy. I will provide an alternative framework and attempt to simplify the model presented by Hornbeck and Keskin (2014) and exploit field-level fixed effects through a Difference-in-Differences model similar in approach to Smith et al. (2017) to identify the causal effect of the LEMA. LEMAs are not tied to county boundaries but rather to areas identified with critical concerns, therefore, it is necessary to describe these policy restriction areas at the field level.

2.2 Water Demand

Currently in the US, as in many other countries, producers obtain a water right to pump groundwater for irrigation. Economists argue that regional markets for these water rights would lead to more efficient use of water and could offset short-run losses due to quantity restrictions resulting in improvements to sustainability of the resources (Rosegrant and Binswanger, 1994; Howe et al., 1986; Hearne and Easter, 1995; Easter and Hearne., 1995; Jr. and Howitt, 1984). In Kansas, as in many other western states, water rights are based on prior appropriation which establishes a hierarchy based on seniority of the water right. In general, economists argue that this misallocates water resources and can cause inefficiencies, for which, water markets seek to correct. With the increased attention on water markets, a large portion of the policy literature that addresses irrigated users is dedicated to the effects of water pricing variation to directly evaluate the impact of a water tax while modeling crop irrigation/production functions and willingness to pay/water rents. (Green et al., 1996; Iglesias and Blanco, 2008; Scheierling et al., 2006; Varela-Ortega et al., 1998; Gómez-Limón et al., 2002; Gómez-Limón and Riesgo, 2004).

The work conducted by Varela-Ortega et al. (1998) estimating the differences in water demand observed in three different water basins was explained by the structural parameters including crop variety, irrigation technology, farm size, and productivity capacity. The study determined different price effects on irrigation water demand, farmers' income, and government revenues while evaluating the changing irrigator strategies on irrigation technology, water management, cropping patterns and land use. The authors indicate that although water pricing policies are regional specific with respect to water conservation strategies and policies have to be carefully defined in each region, the different pricing policies produce remarkably uniform effects across regions and water districts such that the ordering of the effects on water demand and revenue loss is maintained across regions and water management districts. Furthermore, to address future water management policies Iglesias and Blanco (2008) proposed a model to evaluate different pricing effects on water demand, environmental indicators, cropping patterns, technology adoption, labor, farmers' income, and government revenues.

There have additionally been other noteworthy studies quantifying important water pricing policy effects evaluating water pricing effects or quantity regulations on the share of water resources and estimation of the "value" of water (Johansson et al., 2002); nonetheless, the current literature is void of studies defining direct policy effects on specific crop production decisions. The policy effects that this study seeks to estimate include irrigation user's decisions on irrigation technology in the face of a more restricted water use right. To explain irrigation technology choices a study by Green et al. (1996) demonstrated that water price is not the most important factor when producers are making choices on irrigation system strategy. In fact, they find that factors relating to the physical characteristics of crop production including weather, crop and soil characteristics are more important and conclude for the need to use farm-level data to determine the effects on irrigation technology choices.

2.3 Decomposed Marginal Estimates and Elasticities

The studies conducted by Moore et al. (1994) and Schoengold et al. (2006) decompose the water demand estimates into extensive and intensive marginal effects. Although they find the majority of the response occurring at the extensive margin (defined as changes to cropping patterns) they indicate that if most of the price response is at the intensive margin (defined as applied water use), then policies that target irrigation intensity or water-saving technologies will be more cost-effective. While the study conducted by Moore et al. estimated crop type, supply, water demand, and land allocation functions for field crops the study by Schoengold et al. (2006) was more narrowly focused on output and irrigation strategy additionally suggesting the majority of the response occurring due to changes in crop type.

More recently, Hendricks and Peterson (2012) estimated irrigation water demand over the Kansas portion of the Ogallala Aquifer in which they further decompose the water demand estimates into an extensive (changes in irrigated acreage), direct intensive (changes in applied water use), and indirect intensive (changes in crop type) margins finding alternatively the majority of the response at the intensive margin due to changes in applied water/acre. They additionally introduce a framework and argument to establish that the fixed effects estimates are unbiased and consistent for the policy variable of interest even though the estimates for the independent variables are not.

The management of water resources can be difficult because official resource, economic and production data are often available at various non-comparable scales (Mallawaarachchi et al., 1996). In the water demand study conducted by Hendricks and Peterson (2012) they found few water management studies utilizing micro data, or data beyond the county level, with the exception of Moore et al. (1994); Schoengold et al. (2006). The goal of this research is to provide estimates of irrigator responses under the LEMA policy and compare to nearby irrigators met with the same weather and political conditions to uncover the decomposed marginal effects from the policy on farmer's choice behavior such that I evaluate the need for farmer-specific and field-specific variables while loosely modeling this study in the spirit of Hornbeck and Keskin (2014).

2.4 Marginal Effects of Crop Yield Estimation

Previous studies that consider the effects of water use on yields are widely centered around deficit irrigation strategies, crop production, and water pricing policy. Although deficit irrigation is in effect a method to reduce water quantities it does not specifically speak to a water quantity restriction. Studies are extremely limited that consider the impacts of a water quantity restriction policy on subsequent irrigator yields.

Additionally, due to increasing drought management, climate variability, and groundwater sustainability, it is important to consider research on outcomes from other water saving policies and the effectiveness of different yield simulation models. For this reason, I consider the following two sections which speak to water policy and the comparison of different simulated models.

In Kansas, Golden and Leatherman (2011) produced more recently a study considering groundwater demand and revenue loss effects on crop production by comparing before and after trends of the Walnut Creek IGUCA in an effort to evaluate how a more sustainable water management policy might affect producer's profits. They concluded that the localized policy resulted in significant reductions in total area groundwater use, a positive effect on the life of the aquifer, but insignificant long run effects on annual irrigated crop revenues.

2.5 Crop Yield Simulation Models

There are many spatial yield models that are used for predicting yields of various agricultural crops including CropSys, AquaCrop, and YieldStat. These models employ various non-linear regression approaches utilizing databases that are well-informed on nutrient loads of different crops. These models, however, are not regional specific and for the purposes of this study which is done at the micro level, I argue that the Kansas Water Budgets are better suited because they have been validated with actual data from the policy area.

The Kansas Water Budget (KSWB) was developed as a yield predictor for both rain-fed and irrigated crops in western Kansas (Stone et al. 1995, 2006; Klocke et al. 2010; Khan et al. 1996). It is the basis for two irrigation management tools; the Crop Yield Predictor (CYP) and the Crop Water Allocator (CWA) provided by extension from Kansas State University for which we use as a comparison to the remotely sensed data. Many studies have validated the use of the KSWB including the study by Klocke et al. (2010) which compared the KSWB results with four years of field research plot data. In contrast to other models, such as the CERES, it relies on inputs of daily maximum and minimum air temperature, crop coefficients, soil water stress coefficients; and plant water stress coefficients to calculate effective ETe which is related to yield by a locally calibrated yield-ETe relationship. The study also provides a nice graphical representation of how the KSWB predicts yields.

Irrigation needs to be allocated among crops, using crop production functions and production costs for optimum economic return Klocke et al. (2010). The Crop Yield Predictor University (b) (CYP) and the Crop Water Allocator University (a) (CWA) were designed as an interactive decision tool to predict crop yields and economic returns for deficit irrigated crops and made available by Kansas State University's Mobile Irrigation Lab. Both the CYP and the CWA use the Kansas Water Budget (KSWB) simulation model to predict crop yields, ETr, ETc, and daily ASW (Klocke et al. 2010; Stone et al. 1995, 2006; Khan et al. 1996).

The KSWB was designed to use average daily values from 30 years of weather data (maximum and minimum air temperature, solar radiation, and precipitation) for each location to calculate ETr, ETc, daily ASW, and crop yields. Klocke et al. (2010) described the technical background and operation of the KSWB and furthermore compared the results from KSWB simulations with data from a field study conducted at Garden City, Kansas during 2005 through 2008. The KSWB was executed with daily weather data and irrigation events from the field study. They showed that: (1) actual field and KSWB yield-ET relationships were almost identical; (2) soil water contents from field data compared well with KSWB results; and (3) KSWB tended to underestimate crop yields relative to fully irrigated yields and ETc as irrigation declined. These differences were attributed to calibrations of the KSWB with historical data from conventional (tilled) management but the field study was managed with no-till techniques.

CYP users can designate potential irrigation schedules to optimize yields and net returns. These schedules can be tested for a range of annual precipitation to find yield and income risks from several input scenarios including wet, average, and dry years; different dates and amounts of irrigation events; inclusion or exclusion of pre-season irrigation (Stone et al. 1987); different soil types; different irrigation system application efficiencies; or different soil water contents before or during the growing season. The Crop Yield Predictor (CYP) and the Crop Water Allocator (CWA) tools derived from the underlying KSWB model can calculate crop-specific yields by combining the effects of weather parameters, crop development during the growing season, water stress from soil water availability, and the crop's susceptibility to stress during four growth periods as described by Klocke et al. (2010).

The functions of interest for this study that are contained in the KSWB are as follows:

$$ETr = 0.078 + 0.0252(MAT)(RAD)\ 2.493 - 0.00214(MAT)$$

where

ETr = reference ET (mm)

MAT = average daily temperature (C)

RAD = average daily solar radiation ($MJ\ m - 2$).

The maximum evapotranspiration (ETm) and actual evapotranspiration (ETa) calculations are as follows:

$$ETm = Kc * ETr$$

$$ETa = Ks * ETm$$

$$= log(ASW + 1)\ log(101) * ETm$$

where

Kc = crop coefficients

Ks = soil water stress coefficients

ASW = available soil water content (%).

A daily drainage function (D), specific to Ulysses silt loam soil, is given by Stone et al. (1987) and described as a function of total soil water content (TSW) measured in mm.

$$D = 42.7\left(\frac{TSW}{729}\right)^{18.06}.$$

Additionally, ETa was adjusted daily using a water balanced equation of total soil water to a depth of 1.8 m (TSW_t) and was represented as:

$$TSW_t = TSW_y + P_y + I_y - D_y - ETa_y$$

where

TSW_y = total soil water at the beginning of yesterday

P_y = the precipitation that entered the soil yesterday

I_y = the irrigation that entered the soil yesterday

D_y = the water that drained out of the soil yesterday

ETA_y = the water extracted out of the soil yesterday.

Finally, the effective ET ($ETe*$) is calculated from the ratio of ETa to ETm with crop specific weights (W_g) that account for water stress during the growing season and is as follows:

$$ETe* = \sum \left[\frac{\left(\frac{ETa}{ETm}\right) * W_g}{100} \right] ETm$$

This is combined with the Yield-ET equations to represent crop specific yields ($Ycrop$) as:

$$Y_{crop} = \alpha_{crop}(ETe*) - \beta_{crop}$$

Or more specifically, they use the linear functions presented by Klocke et al. (2010) to estimate yields for corn and soybean $Y\ [Mg\ ha^{-1}]$ as a function of $ETe(mm)$ such that the crop-specific yield function is as follows:

$$Y_{corn} = 0.042(ETe*) - 12.33,$$

$$Y_{soybean} = 0.011(ETe*) - 2.39.$$

Chapter 3 - Conceptual Model of Irrigator Water Use Decisions

I conceptually model the effect of the LEMA policy on total acres irrigated, acreage planted to different crops, and irrigation intensity as different margins of adjustment similar to the study conducted by Hendricks and Peterson (2012). Here I apply the same methodology to responses from a water quantity restriction from the Sheridan 6 LEMA. I decompose the effect of the quantity restriction into the following three direct and indirect margins of adjustment: (i) extensive (irrigated acreage), (ii) indirect intensive (changes in crop allocation), and (iii) direct intensive (changes in irrigation intensity for a given crop). My decomposition follows the same methodology as used in the water demand literature that examines the margins of adjustment to changes in price (Moore et al., 1994; Schoengold et al., 2006; Hendricks and Peterson, 2012).

Assume we have a representative irrigator such that their water demand for a particular well is subject to a water quota denoted q. I identify a particular land use as the varying combination of crop type and irrigation technology and represented as $j = 1, \ldots, J$ land uses. Let irrigators choose $a(q)$ the optimal irrigated acreage, and let $w_j(q)$ indicate the optimal applied water intensity in acre inches/acre for each of the j land uses. Let $s_j(q)$ represent the optimal share of irrigated acreage for each land use. I can then define the average applied water per acre as:

$$w(q) = \sum_{j=1}^{J} s_j(q) w_j(q)$$

Here I am only interested in modeling water demand as a function of the LEMA water quota restriction. I represent total water use at the field level as a function of the total quantity of irrigated water and written as a function of average applied water per acre multiplied by the number of acres irrigated:

$$D(q) = w(q)a(q)$$

I can then differentiate the above equation and multiply by $q \,/\, (D(q))$ to give the extensive marginal effects such that I can quantify the change in irrigated acres $\mu_{a(q)}$ and the total intensive marginal effect, the change in irrigation intensity $\mu_{w(q)}$ due to a change in the water quota of the LEMA and represent the elasticities:

$$D'(q)\frac{q}{D(q)} = w'(q)\frac{q}{D(q)} + a'(q\frac{q}{D(q)})$$

or more simply

$$\mu_{D(q)} = \mu_{w(q)} + \mu_{a(q)}$$

Additionally, I can find from decomposition of the average applied water per acre function $w(q)$ the direct and indirect intensive marginal effects or the changes in crop allocation due to a change in the water quota of the LEMA. Differentiating $w(q)$ and multiply by $q \,/\, (w(q))$ such that:

$$\mu_{D(q)} = \left[\sum_{j=1}^{J} s_j(q) w'_j(q) + \sum_{j=1}^{J} s'_j(q) w_j(q)\right] \frac{q}{w(q)}$$

or rather

$$\mu_{w(q)} = \mu_{ww} + \mu_{ws}.$$

Here I find the total intensive margin is made up of two effects μ_{ww} which can be described as the direct intensive marginal effect and μ_{ws} defined as the indirect intensive marginal effect. The indirect marginal effect represents the change in water intensity because farmers switched to less water-intensive crops. The direct intensive effect represents changes in water intensity due to less water application per acre while holding constant the cropping pattern.

Chapter 4 - Data

This analysis merges various spatial data sets to create an unbalanced panel data set for irrigated farms in northwest Kansas across a 6 year period (2009-2014) to describe the effects on farmers' decisions and subsequent production yields from the LEMA. Because LEMAs are not tied to county boundaries but rather to areas identified with critical concerns, it is important to construct the data set at a micro level instead of county-level aggregates.

4.1 Water Use and Agricultural Variables

Kansas law requires all water right holders to report annually on irrigation and crop characteristics (Hendricks and Peterson, 2012). Because of this, I am able to quantify reported water use data at each irrigator's water well (termed a "point of diversion"). Each water right holder is assigned a water right id number which is attached to a specific point of diversion and a specific place of use, however, this does not necessarily mean that the water right is exclusive to just one point of diversion. Because the water use restriction is placed on the water right itself, I aggregate the linkages to identify the variables in the model for water withdrawal, crop type and irrigation system to the water right level from the Kansas Water Rights Information System Database (WRIS). These observations were then identified spatially according to the location of the points of diversion associated with each water right.

The specific crops considered in this analysis include alfalfa, corn, sorghum, soybeans, and wheat with two additional categories identified as multiple and other.

Although there were many crops grown inside the LEMA, there are relatively few water rights that are specifically dedicated to one crop other than corn, therefore, we can only predict yields for single crops where the entire water use is dedicated to the water right.

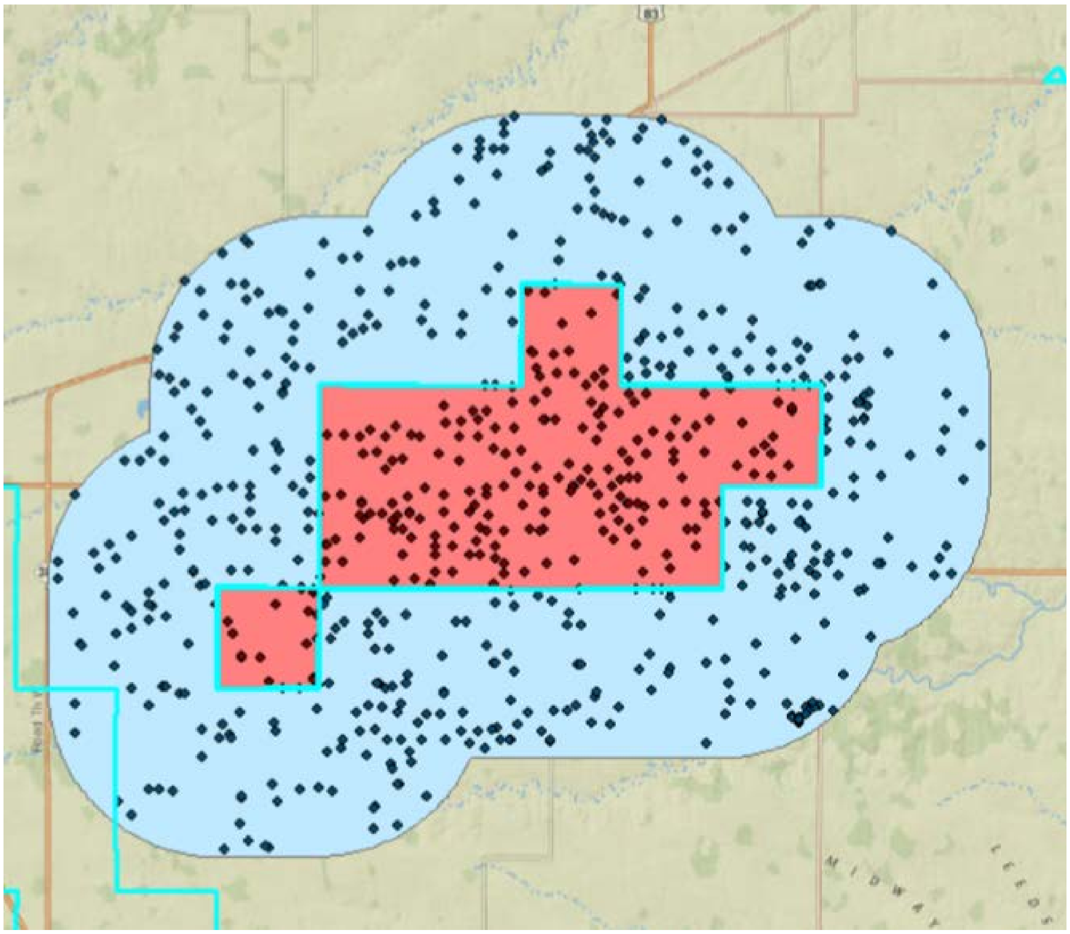
The category for other irrigated uses includes fruits, vegetables, sunflowers, golf courses, pasture, cotton, athletic fields, turf grass, barley, oats, rye, and dry beans. Additionally, some reporting merely indicates that "multiple" crops were grown, but not which crops were specifically grown. The Kansas data does not indicate the number of acres planted to each crop nor how the irrigated water was distributed to each crop when multiple crop types were reported. I, therefore, follow the methodology of Hendricks and Peterson (2012) to identify that if k crops were grown, the proportion of the field in each crop is simply $1/k$. The irrigation technologies in this analysis include flood, drip, center pivot, center pivot with low drop nozzles, and other sprinkler types.

4.2 Weather Controls

Additional site specific variables were obtained to describe yields as a function of water use intensity at each point of diversion. This accounts for site specific yield-ET relationships across farmers within the LEMA boundaries to be computed and compared to farmers outside the boundary based on net irrigation. Because irrigation decisions rely heavily on weather conditions I include a set of weather controls in the model obtained from the PRISM Climate group (PRISM). The PRISM data are a 4 kilometer interpolated grid and have been shown to be an accurate representation of US climate. Because the LEMA is approximately 99 square miles (160 square kilometers) this data provides variability between the LEMA and control groups. Additionally, I include annual precipitation and reference evapotranspiration (ET) to account for changes in water demand due to weather.

4.3 Construction of the Boundaries

The points of diversion inside the LEMA boundary and points of diversion in a 5 mile buffer outside the LEMA boundary are represented as the 2 groups of irrigators for comparison. Wells under the LEMA quantity restriction were identified from official Kansas Department of Agriculture data. The 5 mile buffer zone surrounding the LEMA acting as the control group was then used as the counterfactual group as the basis for a Difference-In-Differences (D-I-D) fixed effect model to evaluate the causal effect on yields from farmers being subject to the LEMA (Figure 4). These boundaries allow us to assess whether yields for the LEMA group would have been the same to the 5 mile group, had the LEMA policy not been in place which is the fundamental assumption of the D-I-D model. Consideration was additionally given to other possible control groups through a series of checks and validations.



Note: The red area indicates wells within the LEMA Policy Area and the blue area indicate wells located in the control group (i.e., 5 Mile buffer area).

Figure 4: Points of Diversion Located Inside the LEMA and the Control Group

4.4 Summary Statistics

This study contains 2819 observations of which 1889 are before the LEMA went into effect. Of those 1889 observations, there were 1175 observations in the 5mile control group and 714 observations in the LEMA treatment group. Following Villa (2012) I use a balancing t-test of the difference in the means of both the dependent variables and covariates between the 5 mile irrigators and the LEMA irrigators in period $t = 0$ based on the kernel weight (Table 1).

None of the estimates on the independent variables indicate a significant difference from each other such that I can identify that there are no pre-policy differences between the two groups. However, I do find significant estimates indicating pre-policy differences in some of the dependent variables suggesting the necessity of the D-I-D framework. I find most LEMA irrigators using a center pivot with low drop nozzles (0.870) followed by a traditional pivot (0.059) or pivot and flood combination system (0.053). Additionally, we can see in this table that most irrigated acreage is dedicated to corn (0.683), with additional land use spread between soybean (0.182), wheat (0.22), sorghum (0.002) and alfalfa (0.013) with the remaining 10% dedicated to other crops (0.008) or multi-crop (0.088) where the exact combination of crop types is unknown. Additionally, I find annual precipitation inside the LEMA to be on average 22 inches and evapotranspiration at 41inches.

Table 1: Summary Statistics of the LEMA Irrigator Group Compared to the 5 Mile Control Group

Variable	Mean 5 Mile (control)	Mean LEMA (treated)	Difference
log Acres Irrigated	4.888	4.887	-0.001
log Applied Inches	7.351	7.434	-0.001**
log Intensity	2.463	2.547	0.084**
Irrigation System			
Flood	0.005	0.004	-0.001
Drip	0.000	0.000	0.000
Traditional Pivot	0.052	0.059	0.006
Pivot with low drop	0.889	0.870	-0.019
Sprinkler	0.003	0.004	0.001
Pivot and Flood	0.043	0.053	0.010
Drip Other	0.005	0.006	0.000
All Other Irr	0.002	0.004	0.003
Cropping Type			
Alfalfa	0.010	0.013	0.002
Corn	0.690	0.683	-0.008
Sorghum	0.003	0.002	-0.000
Soybean	0.188	0.182	-0.006
Wheat	0.021	0.022	0.001
Other Crops	0.009	0.008	0.013
Multiple Unknown	0.076	0.088	-0.068
Weather			
Precipitation	21.741	21.674	-0.068
Evapotranspiration	41.096	41.084	-0.012

4.5 Yield Data

Since I do not have data on actual yields in each field, I generate predicted yields for a given amount of precipitation and irrigation from output created by the KSWB. Although many irrigators maintain rotating crops or have a mix of crops for a single water right, we only want to predict yield estimates for crops where a single crop was planted to the entire water right. In these cases, we know that all the water applied went to the same crop type and can accurately be modeled. Because of the nature of the policy and crops grown in the area there were only enough observations to predict corn and soybean yields. I represent the crop yield as a nonlinear function of net irrigation and precipitation such that:

$$Y^{Irr} = \beta_0 + \beta_1 * Irr + \beta_2 * Irr^2 + \beta_3 * Precip +$$
$$\beta_4 Precip^2 + \beta_4 * (Irr * Precip).$$

Using the data for yield simulations reported in Stone et al., (1995) we generate the necessary coefficients for the nonlinear function of irrigation and precipitation variables in the non-linear model to generate the predicted values of yields to use in the model.

Table 2: Predictive Model of Irrigation and Precipitation for Yield Estimates

Cropping Type	Corn	Soybean
Variable/Statistic		
Const	-182.92**	-55.24**
	(12.57)	(2.75)
Irr	25.56**	8.19**
	(0.374)	(0.089)
Irr^2	-0.43**	-0.13**
	(0.009)	(0.002)
Precip	12.60**	4.13**
	(1.557)	(0.341)
$Precip^2$	-0.05	-0.02
	(0.048)	(0.011)
*Irr*Precip*	-0.43**	-0.15**
	(0.019)	(0.004)
N	275	253
R^2	0.9893	0.9951

Note: The dependent variable is given by the column heading. Parentheses denote robust clustered (water right level) std. errors. ∗ and ∗∗ denote significance at the 5% and 1% levels. Farmer-Time specific estimates were removed for conciseness. LEMA effect estimates adjusted for log-linear correction only.

Figures 3 and 4 shows a visual plot of the fitted values of the specified yield functions for Corn and Soybean, respectively, to the Stone data to identify how well the function fits the original data. Note that there are eleven separate fitted lines shown for different values of precipitation such that I model a range (11 to 21 inches) of possible precipitation scenarios. We can see that there is a nonlinear relationship between the fitted values and the intensity. In general, we can see that the yield estimates increase as an irrigator's water use intensity increases, however, the they do so at a declining rate such that excessive water use intensity results in loss of yields. This intuitively makes sense. Overall, the estimated functions fit the data very well as can be seen visually, and also apparent from the R^2 values of 0.989 and 0.995.

I then use the yield functions in table 2 to predict the yield for every water right planted completely to either corn or soybeans. I assume that the net irrigation is 90% of the total water applied to account for some evapotransiration and system loss since I do not know actual losses. We use these predicted yields from these functions to then estimate how the LEMA impacted crop yields.

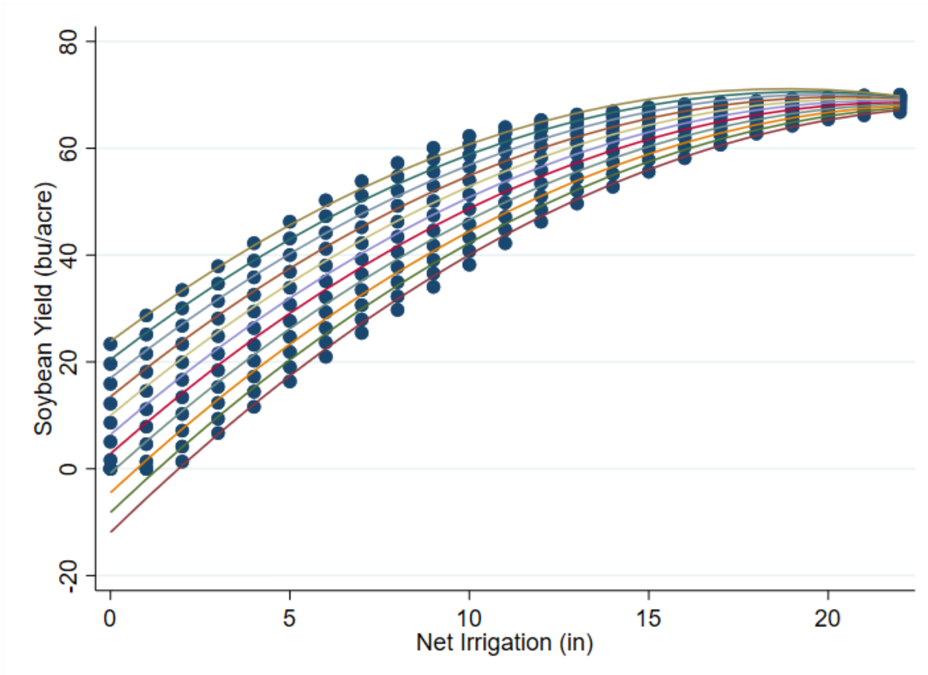


Figure 3: Fit of Corn Yield Model of Net Irrigation at Various Levels of Precipitation

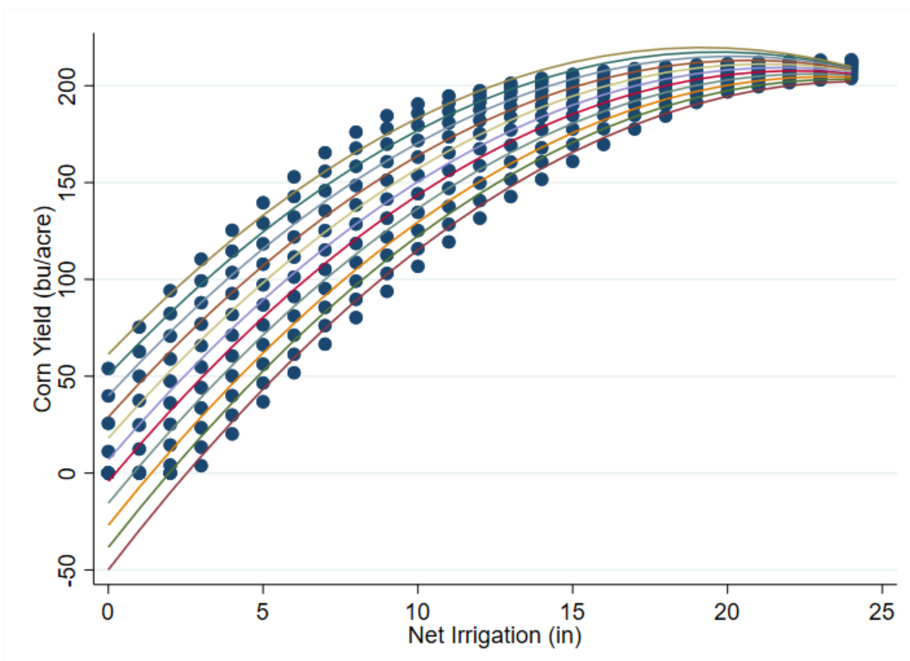


Figure 4: Fit of Soybean Yield Model of Net Irrigation at Various Levels of Precipitation

Chapter 5 - Empirical Methods

5.1 Difference-In-Differences

The Difference-In-Differences estimator allows us to model the unobserved variability across both irrigators and time that is constant. This is shown graphically in the following Figures 5, 6 and 7.

Consider just the difference in behavior of the LEMA irrigators average post-policy compared to a pre-policy average response of the same (Case 1: Figure 5). Here I exploit only the change of water use decisions and effects on yields before and after the LEMA policy went into effect to capture the irrigator fixed effect, however, it doesn't account for changes across time such as weather.

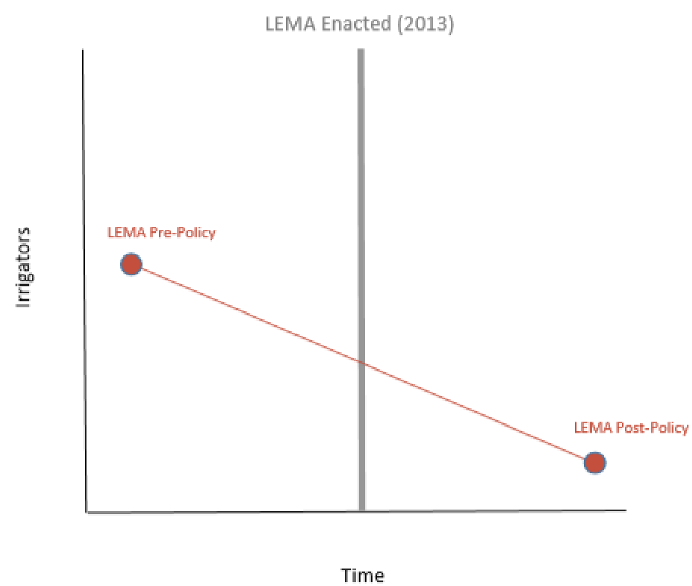


Figure 5: Case 1: Before and After Comparison

Now consider rather just the difference in behavior of the LEMA irrigators in post-policy compared to other nearby irrigators located in a 5 mile radius surrounding the LEMA (Case 2: Figure 6). This exploits the change in water use decisions and effects on yields of LEMA irrigators compared to Non-LEMA irrigators and captures the time fixed effect, however, this does not capture any variability that is specific to just the LEMA irrigators. That is, is there something different about the irrigators themselves that may cause them to naturally use more or less water than other irrigators?

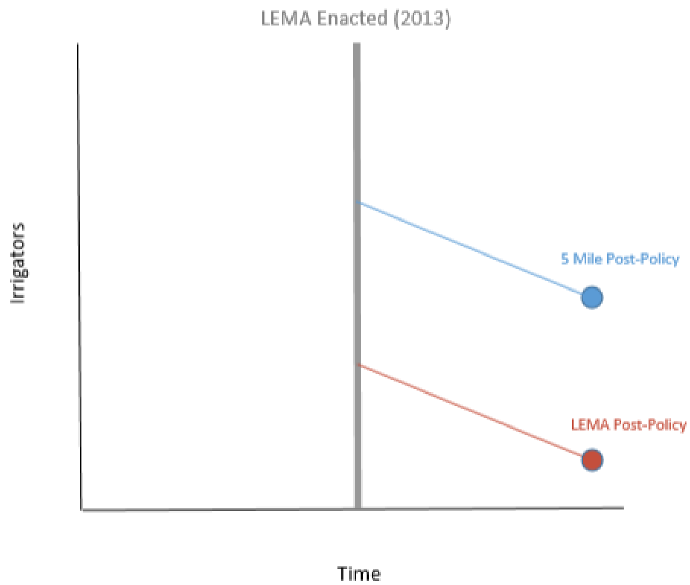


Figure 6: Case 2: Treated and Control Comparison

If I combine the above two scenarios I can effectively model not only how LEMA irrigators changed their behavior pre/post policy but also how that change is different from the change that occurred in another non-LEMA group (Case 3: Figure 7). Essentially I can parse out common effects to both groups to isolate the specific effect of the LEMA policy on the LEMA irrigators by isolating both a time fixed effect as well as an irrigator fixed effect.

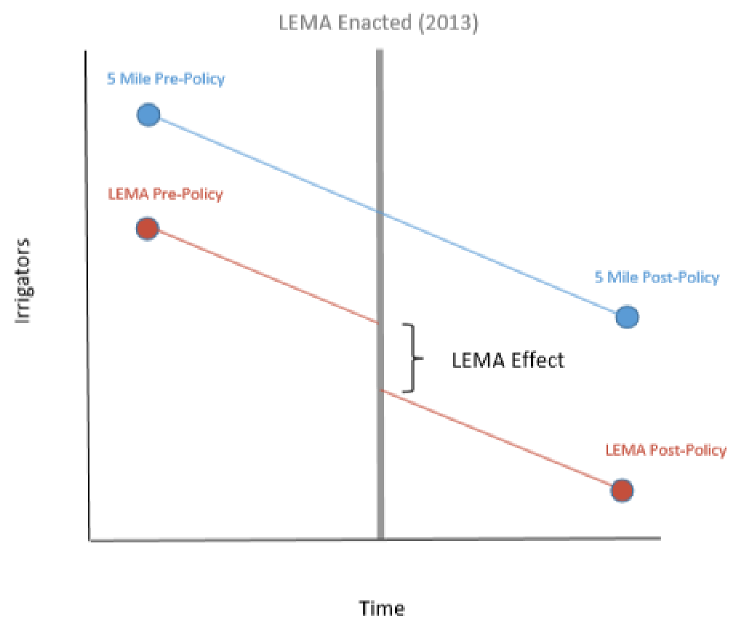


Figure 7: Case 3: Difference-In-Differences

I use D-I-D to evaluate the difference of the short-run effect of the LEMA on farmers' water use behavior and production such that I control for unobserved heterogeneity of water rights that are constant over time and unobserved heterogeneity of each year that are constant across fields.

Consider the on-farm water use decisions (Y_{0it}) made by an irrigator i for a particular water right associated with a particular well location where in the absence of the LEMA, the irrigator's on-farm decisions are determined by the sum of a time-invariant water right effect (α_i) and a yearly effect captured by (δ_t) that is common across all fields. The dependent variables for each irrigator include ($ln(a_{it})$) log acres irrigated, ($ln(w_{it})$) log of water intensity, ($ln(y_{it})$) log of yields dedicated to a single crop, and proportion planted to each (S_{it}) crop type. I represent the potential outcome of not being subject to the LEMA, (i.e. the untreated group) as an expectation that is assumed to be constant over time:

$$E[Y_{0it}|l, i, t] = \alpha_i + \delta_t$$

where Y is the outcome variable of interest, $l = 1$ assigns irrigators to the LEMA, and t indicates years from 2009-2014 such that years can be categorized as either pre-policy or post-policy. Let the dummy variable (D_{lt}) $= 1$ if the irrigator is inside the LEMA boundary after the LEMA restrictions were implemented (i.e., 2013-2014). I incorporate the effect of the policy into the empirical model as follows:

$$E[Y_{1it}|l, i, t] = \alpha_i + \delta_t + \beta D_{lt}$$

The treatment effect of being subject to the LEMA is just the difference of the above two equations representing the parameter β defined as follows:

$$\beta = E[Y_{1it} - Y_{0it}].$$

I can represent the D-I-D using 2 time periods of data, that is before and after the LEMA, as the conditional expectation function such that the difference for the LEMA group pre and post-treatment are as follows:

$$E[Y_{1it}\,|l = 1, t = post] - E[Y_{1it}\,|l = 1, t = pre] = \delta_{post} - \delta_{pre} + \beta.$$

Similarly, I can represent the difference for the control group, those irrigators located just five miles outside the LEMA boundary as the following conditional expectation function:

$$E[Y_{0it}\,|l = 0, t = post] - E[Y_{0it}\,|l = 0, t = pre] = \delta_{post} - \delta_{pre}.$$

The aggregate causal effect of interest (β) can be obtained by taking the difference in the differences as follows:

$$\{E[Y_{1it}\,|l = 1, t = post] - E[Y_{1it}\,|l = 1, t = pre]\}$$
$$- \{E[Y_{0it}\,|l = 0, t = post] - E[Y_{0it}\,|l = 0, t = pre]\} = \beta.$$

I will show D-I-D results for the key outcomes of interest using aggregate (average) data across the water rights inside the LEMA boundary and the 5-mile buffer. I consider these aggregate results as useful descriptive results, however, because of the restrictive assumptions of the D-I-D it is important to explore other variability in an expanded fixed effects model that allows for changes across time and space simultaneously.

The D-I-D model isolates changes across time that are constant in space, and changes in space that are constant in time. In order for our D-I-D model to be correctly specified, there must no systematic differences among our irrigators in our treatment group from the irrigators in our control group. That is, I assume that both groups follow a parallel path such that when something changes in one group it also changes in the other simultaneously. This assumption allows isolation of any differences in the trends as being a causal effect due to the treatment. However, it is important to note that this assumption hinges on having no systematic differences among the groups of irrigators due to other non-LEMA effects.

5.2 Preferred Fixed Effects Model

I argue that although the D-I-D framework is useful to identify general outcomes of the LEMA policy, it is important to account for the differences of each farmer in each year in order to accurately measure the causal estimate. For this, I identify the following less restrictive fixed effects model such that I control for unobserved heterogeneity of water rights that are constant over time, unobserved heterogeneity of each year that are constant across water rights, and unobserved heterogeneity of farmers that varies across years. Because the D-I-D isolates the difference as being due to the LEMA, I relax the assumption to allow for isolation of other non-LEMA differences among irrigators.

The dependent decision variables for each irrigator now represented as the potential outcome of not being subject to the LEMA, includes a farmer-time effect (λ_{ft}) and a vector (Z_{it}) of weather controls such that our previous time fixed effect δ_t is now captured in λ_{ft}:

$$E[Y_{ift}|l, i, f, t] = \alpha_i + \beta D_{lt} + \lambda_{ft} + \theta Z_{it}$$

Note that I can still isolate the effect of the LEMA water policy (D_{lt}) while introducing the farmer-time fixed effects because some farmers manage water rights inside the LEMA boundary and in the 5-mile buffer. Intuitively, my econometric model exploits behavior changes of farmers who manage water rights both inside and outside the LEMA such that their irrigation behavior for water rights inside the policy boundary were different than water rights just outside the boundary.

An important consideration of this research is on the underlying assumptions of our model. It is important to consider possible sources of selection bias or misspecification in the model. Selection bias can be in many forms such that the selection of individuals contained within a specified group are not selected randomly and prohibits inference of a causal policy effect and the measures of marginal effects would be biased.

For example, if farmers in the LEMA sample group chose to be in the LEMA, then we know that they could potentially differ systematically from farmers who did not choose to be in the LEMA and might respond to the policy differently. In order to address this concern, I want to validate that the fields inside the LEMA boundary are not systematically different from those outside the boundary and that the control group is not systematically different from another possible control. This can be done by comparing pre-treatment trends of both groups, specifically to identify that our counterfactual argument, that irrigators would have acted in the same way as our control group, is substantiated. I will compare the control group to an additional spatially identified 10 Mile group to establish the validity of the 5 mile control and uncover any possible issues related to selection bias.

In addition, I will test the need for additional explanatory covariates including weather and irrigator trends. It is important to correctly specify the model such that I can be confident in my interpretations of the causal effect of interest from the LEMA policy and to establish that the model is free from endogeneity issues and not misspecified.

5.3 Decomposing the Marginal Effects of Water Use

I obtain estimates of the total extensive margin estimates (βa) and the total intensive margin estimates (βw) directly from the following log-form regressions for the effects on irrigated acres $ln(a_{ift})$ and intensity of applied water per acre $ln(w_{ift})$:

$$ln(a_{ift}) = \alpha_i + \beta_a D_{lt} + \lambda_{ft} + \theta X_{ilt} + \epsilon_i^a \qquad (1)$$

$$ln(w_{ift}) = \alpha_i + \beta_w D_{lt} + \lambda_{ft} + \theta X_{ilt} + \epsilon_i^a \qquad (2)$$

where

α_i is a water right fixed effect

λ_{ft} is a farmer-time fixed effect

X_{ilt} is a vector of precipitation and evapotranspiration variables

However, I assume that heterogeneity of soils and hydrological variables are constant across time such that they will be captured in the α_i. So that, I can simply characterize the direct intensive marginal effect in response to the policy, in estimates form, as β_y and the total effect on water use in response to the policy is simply the sum both margins, our estimates obtained from equations (1) and (2).

$$\hat{\beta}_a + \hat{\beta}_w = \hat{\beta}$$

I characterize the intensive margin of water use as having both a direct and indirect effect. I estimate the direct intensive margin by holding land use constant in our regression. Denote $\boldsymbol{S_{it}}$ as a vector of variables indicating the share of irrigated acreage for each land use where land use includes the combination of crop and irrigation technology. The direct intensive margin of water use is estimated from the following regression:

$$ln(w_{ift}) = \alpha_i + \beta_{ww} D_{lt} + \lambda_{ft} + \theta X_{ilt} + \rho \boldsymbol{S_{it}} + \epsilon_{it}^{a}. \quad (3)$$

Hendricks and Peterson (2012) show that we can recover the indirect intensive margin as simply the difference between the total intensive margin and the indirect intensive margin.

$$\hat{\beta}_w + \hat{\beta}_{ww} = \hat{\beta}_{ws}$$

5.4 Estimating the Effect on Crop Yields

Additionally, utilizing the same framework I can further obtain estimates of the total effect on yields (β_y) directly from the following log-form regression.

$$ln(y_{ift}) = \alpha_i + \delta_t + \beta_y D_{lt} + \theta X_{ilt} + \epsilon_{it}$$

5.5 Event Study

Conceptually, an event study examines how the effect of the policy varied across different years rather than just a 2 period (pre and post) aggregate to uncover the variability of each year. It applies the same strict assumptions that decisions among water right holders in the LEMA would be expected to be the same as water right holders in the 5 mile control group if the water policy had not been implemented (i.e. the counterfactual scenario) such that the water use decisions in a given year represent the difference between the observed behavior (Y_{1ift}) in that year and the observed behavior of the control group (Y_{0ift}).

I consider the impact of the LEMA policy event on the total extensive (i.e. changes in irrigated acres) and total intensive (i.e. changes in applied water intensity) margins. I represent the effects on the log-linear prediction of the total extensive marginal $ln(a_{it})$, total intensive marginal $ln(w_{it})$, and direct intensive estimates in the following regressions such that I can separate the effects of each year on the linear predictions graphically.

$$ln(a_{ift}) = \alpha_i + \sum_{m=2010}^{2014} \beta_m D_{lt}^m + \lambda_{ft} + \theta X_{ilt} + \epsilon_{it} \tag{4}$$

$$ln(w_{ift}) = \alpha_i + \sum_{m=2010}^{2014} \beta_m D_{lt}^m + \lambda_{ft} + \theta X_{ilt} + \epsilon_{it} \tag{5}$$

$$ln(w_{ift}) = \alpha_i + \sum_{m=2010}^{2014} \beta_m D_{lt}^m + \lambda_{ft} + \theta X_{ilt} + \rho \boldsymbol{S_{it}} + \epsilon_{it}^a. \tag{6}$$

where $D_{lt}^m = 1$ if the LEMA restriction was applied to the water right and $t = m$. Therefore, the estimate for β_m indicates how water use changed for water rights inside the boundary compared to the change in the 5-mile buffer in year m compared to a baseline year in 2009.

5.6 Dummy Correction for Log-Linear Models

In his paper, Giles (2011) describes some of the errors that can arise if we improperly interpret our coefficient on the treatment dummy variable. He identifies the particular post-transformation that must be applied in order to accurately interpret the coefficient of a continuous regressor in a regression model, where the dependent variable has been log-transformed as follows:

$$D'_i = [e^{\beta} - 1]$$

where β is the coefficient for the LEMA policy effect if our causal effect switches from $D_i = 0$ to $D_i = 1$. I include this correction on the subsequent estimates unless otherwise specified.

5.7 Robust Clustered Standard Errors

I additionally consider my assumptions of the model, the estimates, and the standard deviation of the underlying errors. I evaluate the use of the following three variance estimators: OLS (1), Robust (2) and Robust Cluster (3).

$$V_{OLS} = \frac{1}{(N-K)} \sum_{i=1}^{N} \epsilon_i^2 * (X'X)^{-1} \tag{7}$$

$$V_{ROB} = (X'X)^{-1} \left[\sum_{i=1}^{N} (\epsilon_i x_i)'(\epsilon_i x_i) \right] * (X'X)^{-1} \tag{8}$$

$$V_{CLUST} = (X'X)^{-1} \left[\sum_{c=1}^{C} (\epsilon_{ic} x_{ic})'(\epsilon_{ic} x_{ic}) \right] * (X'X)^{-1} \tag{9}$$

where X is a $m\ x\ n$ matrix, i is the residual for the ith observation and x_i is a row vector of predictors including the constant. The formula for the clustered estimator is simply that of the robust (unclustered) estimator with the individual $\epsilon_i x_i$ replaced by their sum of squares over each cluster.

I assume that there exist well-specific characteristics that might carry across time. Something fundamentally different about the well itself that would cause water use to be impacted, this could include impacts from the user, or impacts from the underlying physical structure of the well, pumping mechanism and hydrology. I can account for this through the use of robust clustered standard errors at the water right level such that I assume independence between water rights, but allow for correlation over time.

Chapter 6 - Results: Extensive and Intensive Marginal Changes in Water Use

6.1 D-I-D Model and Visual Analysis

Using the D-I-D framework we can use the aggregated data to estimate the before and after average difference inside the LEMA and compare to the before and after average difference in the 5 mile buffer zone outside the LEMA to quantify how irrigators under the LEMA responded in quantity of irrigated acreage for each crop planted compared to irrigators located within the 5 mile boundary. Figure 8 shows the graphical results for total acres irrigated (extensive margin) and Figure 9 indicates the effect on water use intensity (intensive margin). I find that irrigators in the 5 mile boundary increased applied intensity slightly, however, if I assume that the same trend would have occurred inside the LEMA in the absence of the restriction then this implies that the LEMA resulted in a 35% reduction in applied inches per acre. The response at the intensive margin is larger than the extensive margin, where the extensive margin only resulted in a 3% decrease in irrigated acreage. Similar results were found using a Bayesian structural time series model reporting a 31% reduction over the 5 year period of the LEMA in Deines et. al. (2019).

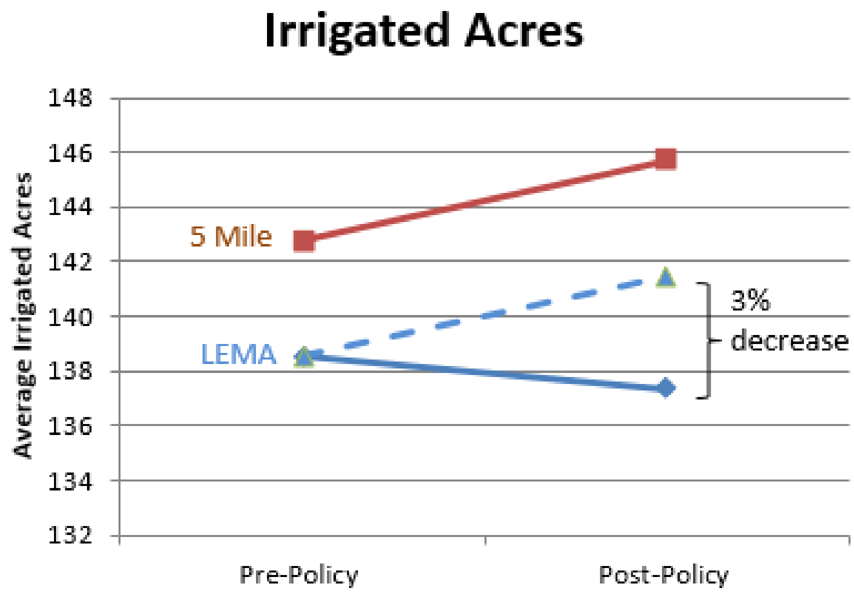


Figure 8: Difference-In-Differences Results for Total Irrigated Acreage

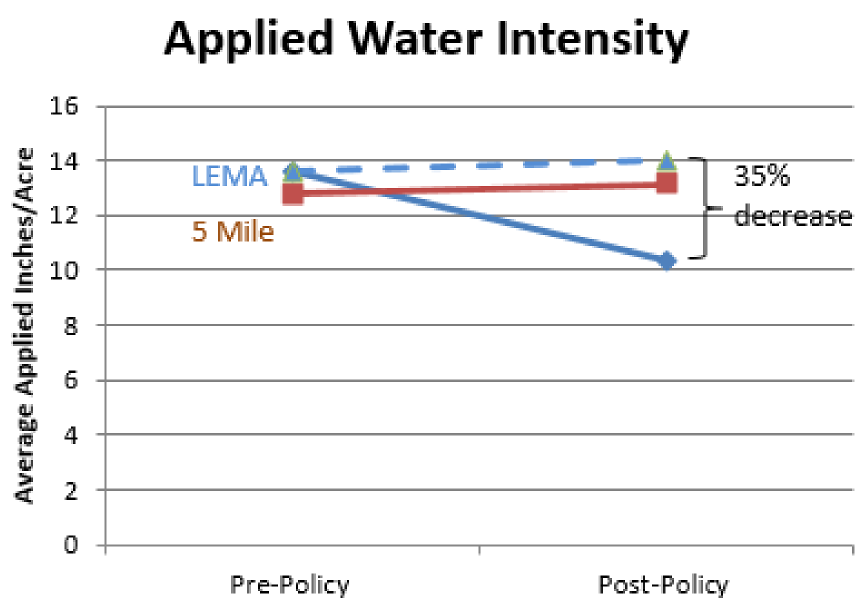


Figure 9: Difference-In-Difference Results for Applied Inches per Acre (Water Intensity)

I additionally consider the crop specific effects from the water policy to identify how irrigators of different crops chose to modify their behavior at the extensive and intensive margins. Again, comparing to the counterfactual scenario, I find that irrigators chose to reduce irrigated acres dedicated to alfalfa (-40%) and corn (-18%). Alternatively, irrigators chose to expand irrigated acreage for sorghum (66%), wheat (7%), multiple unknown (17%), and soybean (5%) after the LEMA policy (Figures 10-15). Irrigators in the 5 mile zone increased irrigated acreage slightly while irrigators in the LEMA boundary decreased irrigated acres slightly.

I also estimate the response of applied water intensity of irrigators for each crop in the LEMA (Figures 16-21). On average, irrigators chose to reduce their applied water intensity. It is important to note that although many water rights had some sort of crop mix, this analysis could only be applied to water rights that were planted to a single crop. The data did not differentiate fields assigned to multiple crop mixes and therefore was limited to only water rights of the same crop type.

Corn and soybean LEMA irrigators primarily responded by reducing average applied water compared to irrigators located within the 5 mile boundary who applied more inches per acre to these crops. The largest reductions were from wheat (-54%) and corn (-46%) followed by alfalfa (-32%), soybean (-28%) and multiple unknown (-16%). The large reduction in multiple crops could be partially attributed to the introduction of less water intensive varieties being added to the crop mix. However, sorghum irrigators chose to increase applied water per acre by 71% after the LEMA policy.

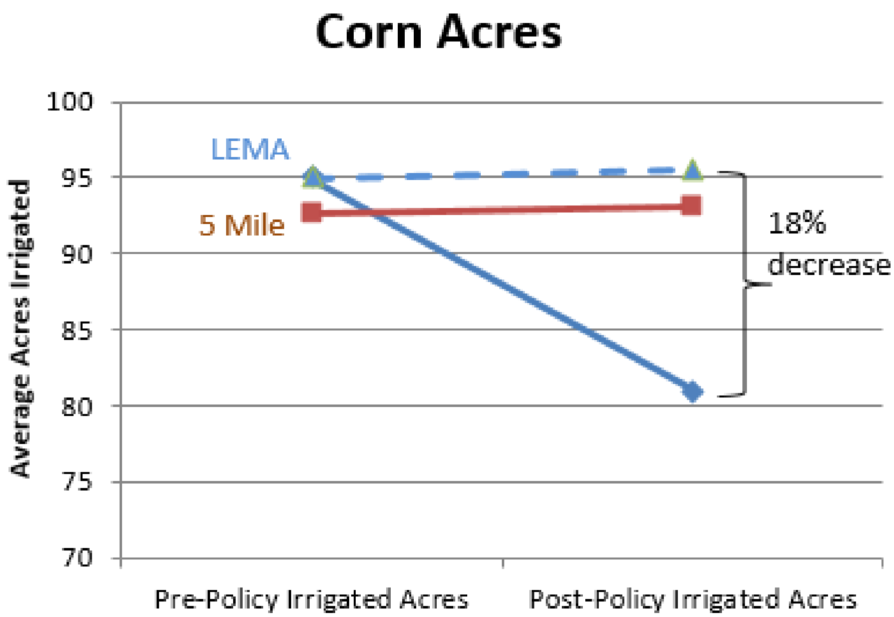


Figure 10: Difference-In-Difference Results for Corn Irrigated Acreage

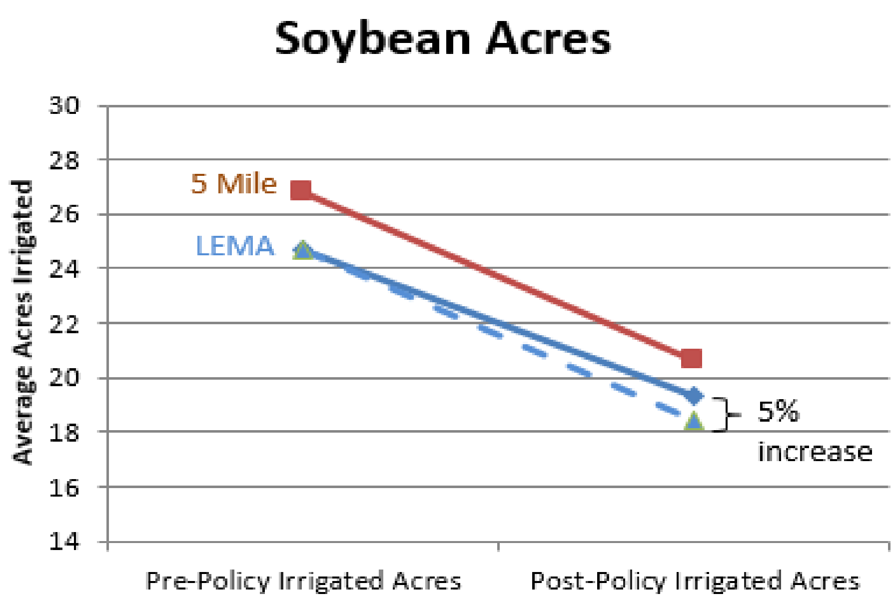


Figure 11: Difference-In-Difference Results for Soybean Irrigated Acreage

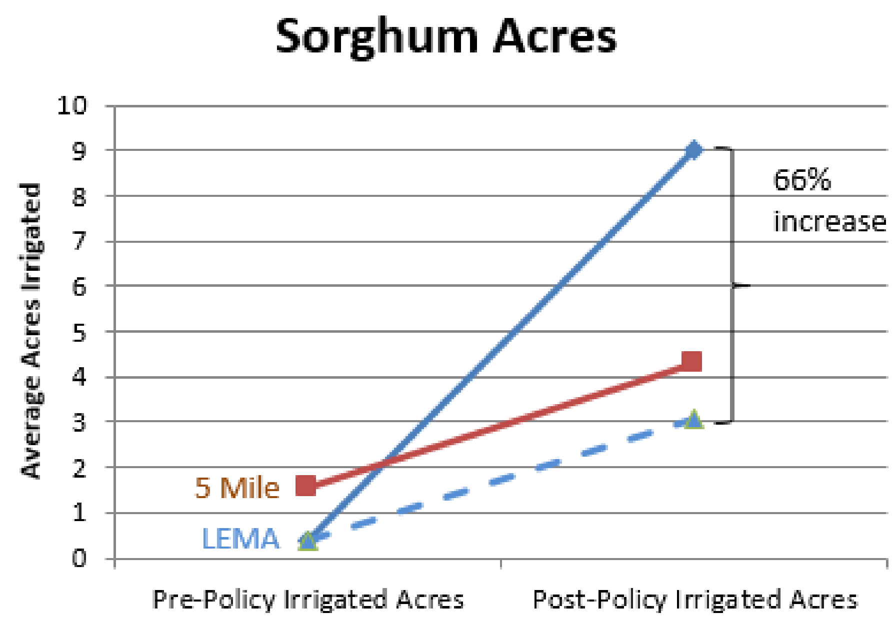


Figure 12: Difference-In-Difference Results for Sorghum Irrigated Acreage

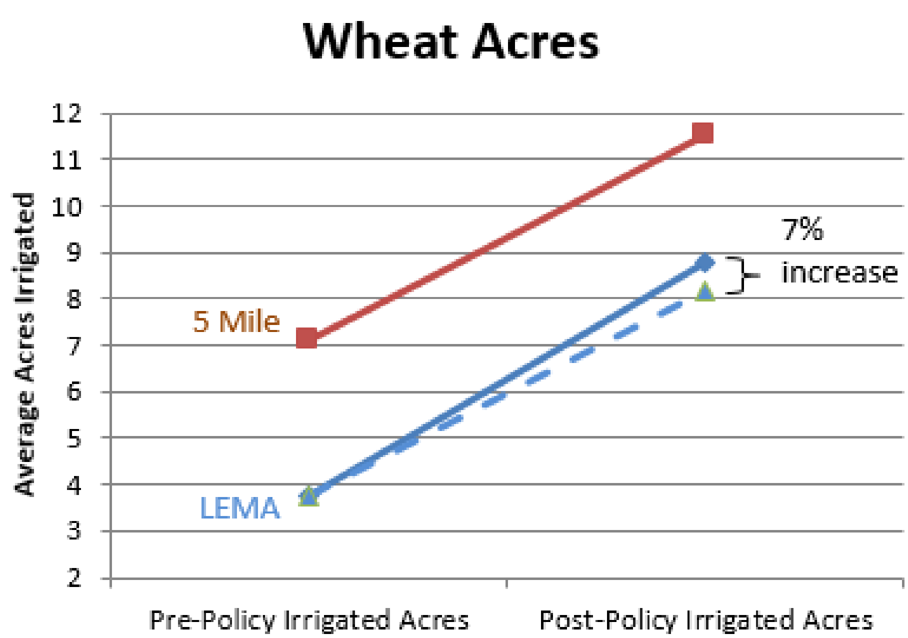


Figure 13: Difference-In-Difference Results for Wheat Irrigated Acreage

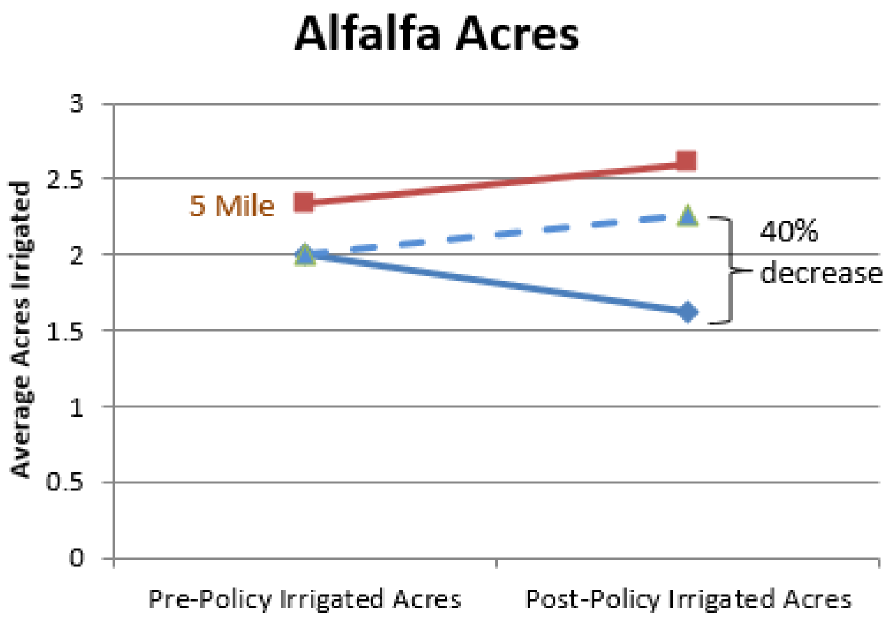


Figure 14: Difference-In-Difference Results for Alfalfa Irrigated Acreage

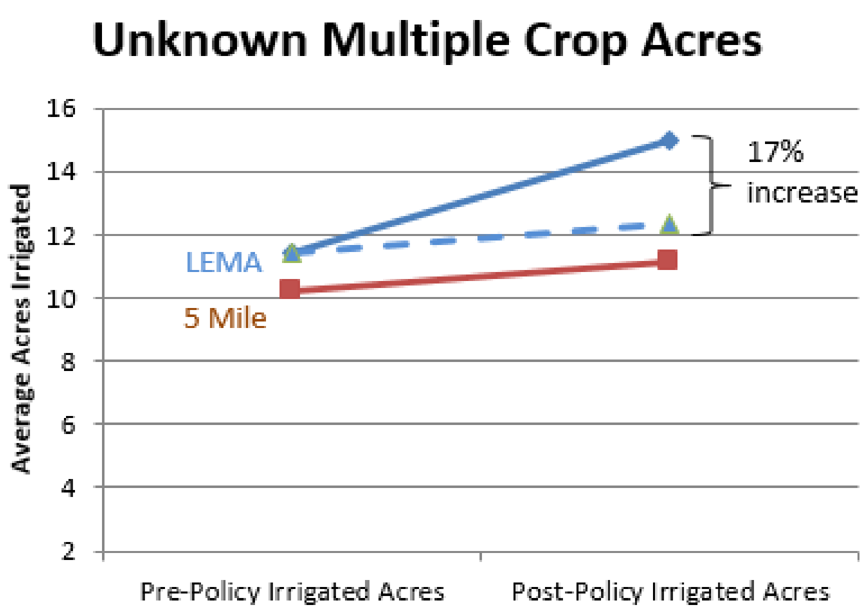


Figure 15: Difference-In-Difference Results for Multiple Crops Irrigated Acreage

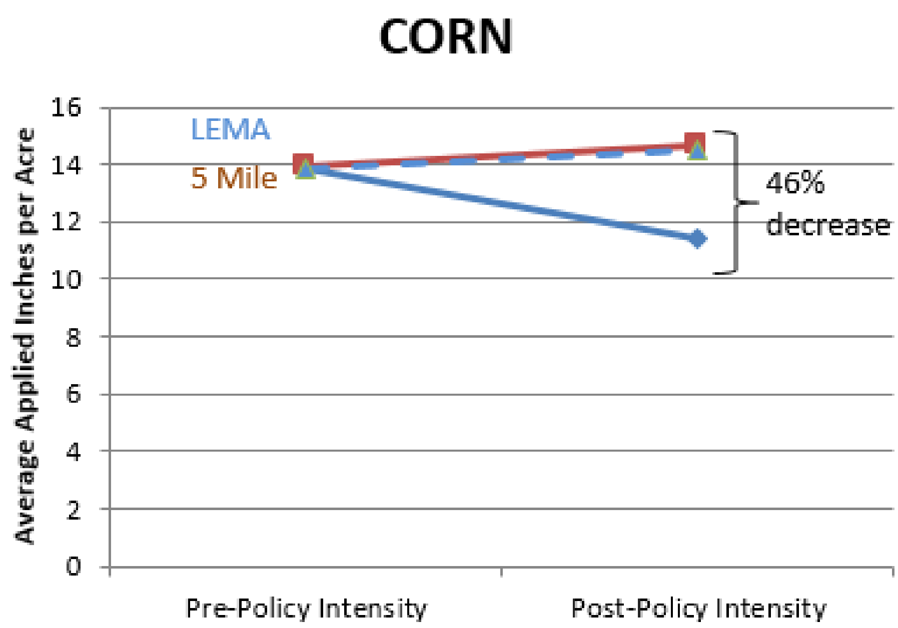


Figure 16: Difference-In-Differences Results for Corn Applied Water Intensity

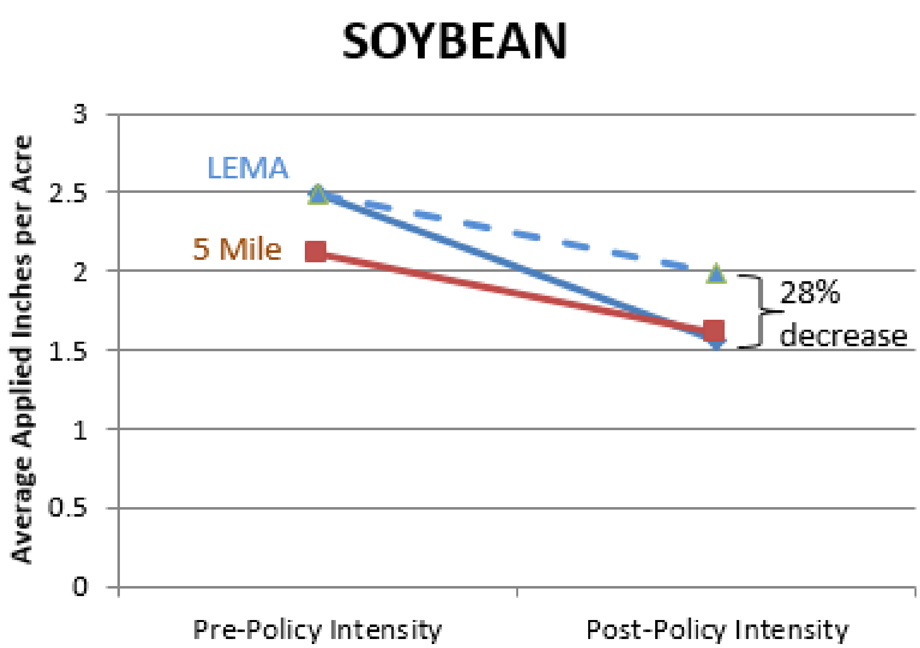


Figure 17: Difference-In-Difference Results for Soybean Applied Water Intensity

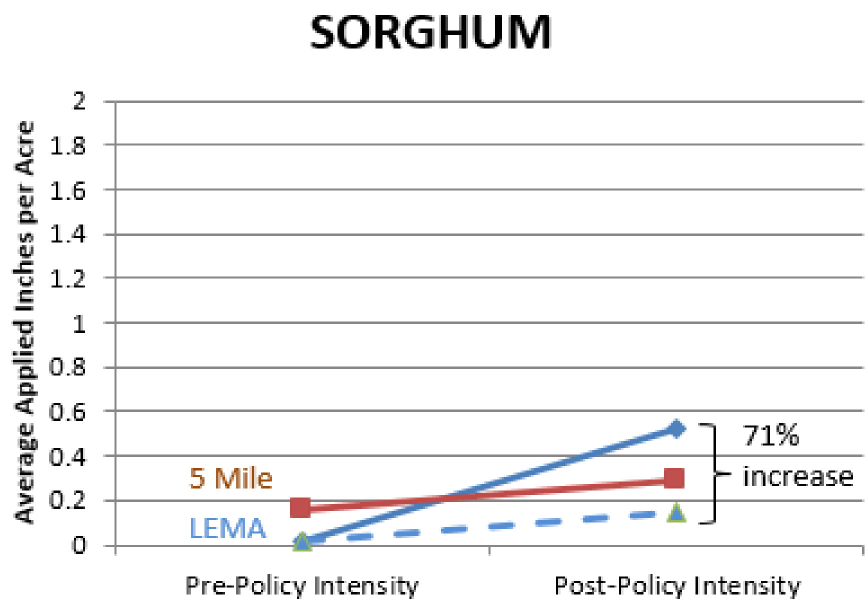


Figure 18: Difference-In-Difference Results for Sorghum Applied Water Intensity

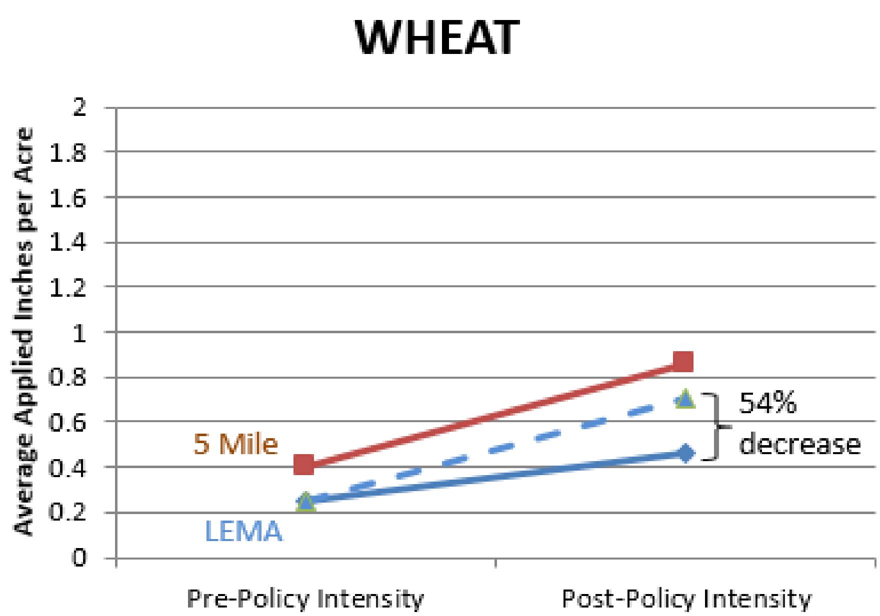


Figure 19: Difference-In-Difference Results for Wheat Applied Water Intensity

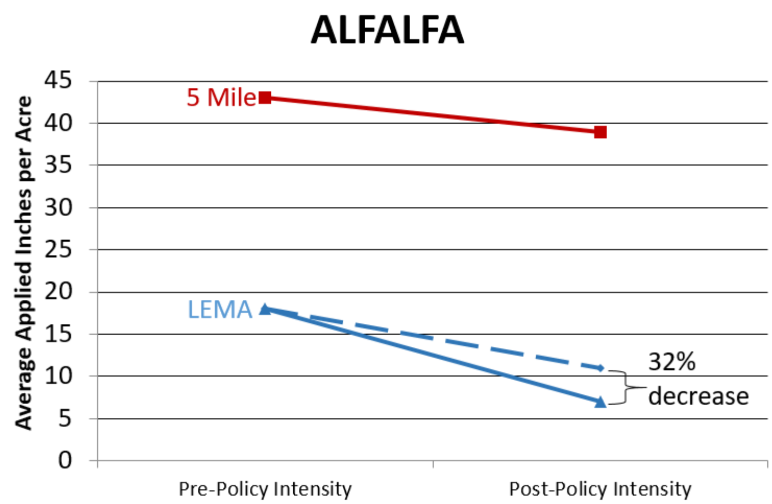


Figure 20: Difference-in-Difference Results for Alfalfa Applied Water Intensity

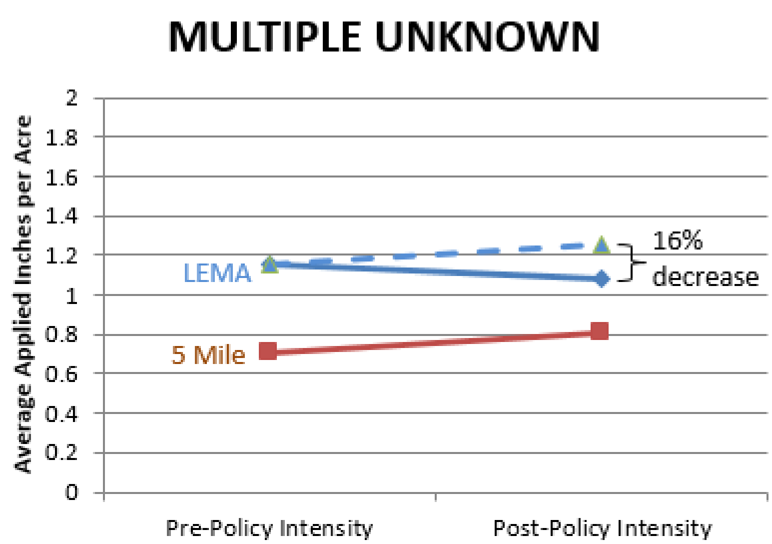


Figure 21: Difference-In-Difference Results for Multiple Crops Applied Water Intensity

6.2 Econometric Results

6.2.1 Preferred Specification

Table 3 reports the set of decomposed marginal effects of water use from the preferred fixed effects regression with the LEMA effect adjusted for the log-linear form where the total extensive, total intensive, and direct intensive estimates are derived from the previous equations (1), (2) and (3), respectively. I find that the estimates are significant at the 1% confidence intervals which implies the LEMA resulted in a reduction in water use through both the number of total acres irrigated (-3.8%) as well as the quantity of applied inches per acre (-21.2%) resulting in an overall water use reduction.

I condition the estimates to include effects from cropping type in order to estimate the direct intensive margin (i.e., holding constant land use). I find the estimates measure of the direct log of water intensity effect (-18.5%) to be only slightly smaller than the total intensive effect (-21.2%) and still significant at the 1% confidence interval such that the larger intensive response occurs at the direct margin indicating little indirect intensive response, i.e. crop switching. I find the expected negative signs on the less water-intensive crops for alfalfa (6.1%) sorghum (-6.3%) and wheat (-22.6%) when compared to crops within the "other" or "multiple crop" category. Additionally, I find positive coefficients for corn (18.5%) and soybeans (6.7%) indicative of our more water-intensive crops. The larger water use intensity is attributed to corn and wheat, however, which are significant to at least the 5% level.

I can now follow Hendricks and Peterson (2012) and back out the indirect intensive marginal effects by simply subtracting the direct intensive from the total intensive margins and find little response (-2.7%) due to changes to cropping patterns.

Table 3: Decomposed Estimates of Marginal Effects of Water Use

	Total Effect	***Extensive***	***Intensive***		
Variable/Statistics		Total	Total	Direct	Indirect
LEMA policy effect	-0.242**	-0.038**	-0.212**	-0.185**	-0.027
	(0.045)	(0.019)	(0.049)	(0.046)	
Cropping Type					
Alfalfa			-0.061		
			(0.119)		
Corn			0.185**		
			(0.069)		
Sorghum			-0.063		
			(0.093)		
Soybean			0.067		
			(0.073)		
Wheat			-0.226*		
			(0.112)		
Weather					
Precipitation	-0.025*	0.010	-0.035**	-0.035**	
	(0.012)	(0.007)	(0.012)	(0.012)	
Evapotranspiration	-0.035	-0.021	-0.014	-0.046	
	(0.082)	(0.038)	(0.082)	(0.075)	
N	2817	2817	2817	2817	
R^2	0.1846	0.0076	0.2422	0.2999	

Note: Parentheses denote robust clustered (water right level) std. errors. ∗ and ∗∗ denote significance at the 5% and 1% levels. Farmer-Time specific estimates were removed for conciseness. LEMA effect estimates adjusted for log-linear correction only.

6.2.2 Water Policy Event Study

The previous model framework has proven useful in the context of isolating the causal parameter of interest, however, I also wish to isolate the effect per year, rather than just a pre/post aggregate estimate. I now consider how lags and leads of the LEMA policy effect impacts our linear estimation whereby an event study (Figure 22 and Table 4) using equations (4), (5), and (6). This approach not only will help to validate my identification strategy but also allow us to see if the response was different in the first year of the LEMA compared to the second to uncover possible adaptation or learning among water right holders.

First, I find that the coefficients pre-policy are not significantly different from zero which signals that my model specification is correct. Additionally, I find that the total marginal effect is influenced by similar reductions in water use in both the policy year (-31.3%) and 2014 (-32.4%) indicating that irrigators may be attempting similar water use modifications year to year that are significant at the 1% level. This doesn't suggest any large adaptation strategies at the extensive margins. However, I also find the primary impact of the extensive margin to be from modifications to acreage in just the policy year (-5.8%) also significant at the 1% level rather than any continued reductions at the extensive margin further post policy. Therefore, it appears that farmers may have learned that reductions in intensity were the least cost method to reduce water use rather than acreage reductions.

Furthermore, at the intensive margin, I find that the effect is again influenced by reductions in the first year after the policy went into effect (-25.5%) with further reductions in 2014 (-30.4%). This could suggest possible adaptation strategies of the irrigators such that they find further room to reduce water use at the intensive margin. Although, these findings are consistent with the short-run (intensive) marginal adjustments of previous studies further review of ongoing water use decisions might indicate if this was due to reduced applied inches/acre or to switching out to less water-intensive varieties (Peterson and Ding, 2005; Pfeiffer and Lin, 2014).

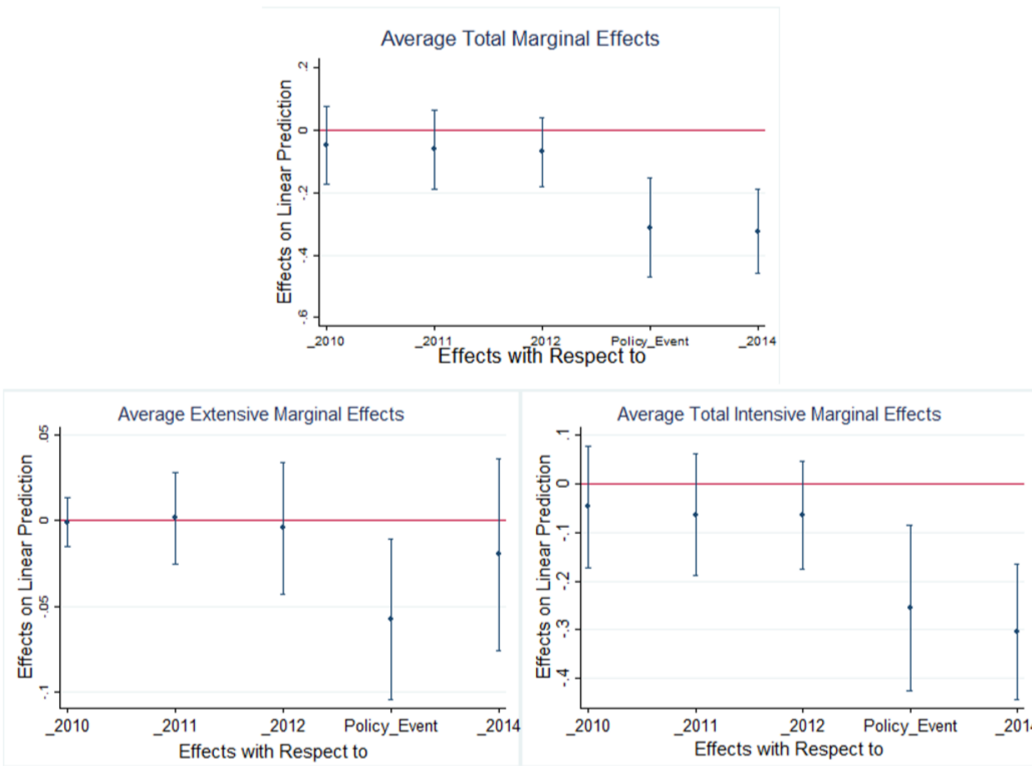


Figure 22: Event Study Results: Average Yearly Impact on Water Use at the Intensive, Extensive, and Total Margins

Table 4: Event Study Coefficient Estimates

Log-form Estimate	2010	2011	2012	2013	2014
Total Effect	-0.048	-0.062	-0.070	-0.313**	-0.324**
	(0.064)	(0.064)	(0.056)	(0.081)	(0.069)
Extensive	-0.001	0.002	-0.004	-0.058**	-0.020
	(0.007)	(0.014)	(0.020)	(0.024)	(0.029)
Intensive	-0.047	-0.064	-0.065	-0.255**	-0.304**
	(0.064)	(0.064)	(0.057)	(0.087)	(0.072)

Note: Parentheses denote robust clustered (well-level) std. errors. $*$ and $**$ denote significance at the 5% and 1% levels. All estimates adjusted for log-linear correction.

6.2.3 Heterogeneous Response among Large Irrigators

A concern of some farmers prior to the LEMA being implemented was that a subset of farmers might have a greater ability to adjust to the water use restriction because they maintained rights on a much larger proportion of wells. That is, they would have the flexibility to move water use between wells and possibly use more water relative to what other farmers would have to do resulting in a disproportionate water use restriction that ultimately restricts smaller firms more.

I evaluate this concern through the use of an additional set of fixed effect regressions of LEMA irrigators with an additional variable to identify the effect of well ownership on applied water intensity and acres irrigated (Table 5). The estimates for log water use/acre $ln(w_{it})$ and log irrigated acres $ln(a_{it})$ are reported from the following regressions:

$$ln(w_{it}) = \alpha_i + \beta_1 D_{it} + \beta_2 D_{it} * Large_i + \lambda_{ft} + \theta X_{ilt} + \epsilon_{it}$$

$$ln(a_{ift}) = \alpha_i + \beta_1 D_{it} + \beta_2 D_{it} * Large_i + \lambda_{ft} + \theta X_{ilt} + \epsilon_{it}$$

where α_i, λ_{ft}, and θ_{it} represent the fixed effects and controls, D_{it} is the LEMA effect dummy variable, and $Large_i$ is the dummy variable for large well ownership if a water right was owned by an irrigator with 2 or more water rights inside the policy boundary (i.e., 2 or more wells inside the LEMA policy boundary).

Table 5: Fixed Effects Regression of Disproportionate Restriction

Variable/Statistics	Total Effect	***Extensive***	***Intensive***
LEMA Policy Effect	-0.262**	-0.067**	-0.210**
	(0.079)	(0.028)	(0.082)
LEMA Large	0.041	0.046	0.005
	(0.095)	(0.036)	(0.102)
N	2817	2819	2817
R^2	0.1834	0.0072	0.2423

Note: The dependent variable is given by the column heading. Parentheses denote robust clustered (well-level) std. errors. $*$ and $**$ denote significance at the 5% and 1% levels. Weather and Farmer-time specific estimates were removed for conciseness. LEMA effect estimates adjusted for log-linear correction only.

I find no statistical evidence that having more than one well could encourage increased water use among those irrigators and lead to a disproportionate water use restriction. Table 5 describes the interaction terms as insignificant at all margins of adjustment while the LEMA policy effect estimates continue to remain robust. I also conducted estimations at varying levels of well ownership (i.e., >2 or more wells) and found that this did not change the significance of the estimates or the interpretation of the results.

6.2.4 Alternative Specifications

While the D-I-D model accounts for unobserved heterogeneity of water rights that are constant over time (i.e. water right-specific differences) and of each year that is constant across fields (i.e. crop, energy, and other input prices) it is important to test for the exclusion of any other additional controls such as the farmer-time fixed effect in the preferred model. To do so, I follow Villa (2012) and apply the D-I-D kernel propensity score matching estimator.

The benefit of the matching estimator (as opposed to my fixed effects estimator) is that it estimates the effect of treatment by comparing changes n outcomes of irrigators inside and outside with similar characteristics (crop type, irrigation technology, etc). That is, the D-I-D matching estimator groups irrigators belonging to a set of covariates and then compares the change in outcomes of irrigators in the LEMA to the change in outcomes of similar irrigators in the control group controlling for the observed differences among irrigators.

I then represent the conditional probability of the LEMA as the propensity score conditioned on set X such that the conditional mean is the weighted average of outcomes when $Di = 0$ and the kernel estimator is represented as:

$$E(Y_{0i}|P(X_i), Di = 0) = \sum_{j=1\{D_j=0\}}^{n_0} W_j\big(P(X_i)\big)Y_{0j}$$

with a weighting assigned as

$$W_j(P(X_i) = \frac{K(\frac{P(X_i)-P(X_k)}{h_n}}{\sum_{k=1\{D_k=0\}}^{n_0} K\frac{P(X_i)-P(X_k)}{h_n}}.$$

In general, the kernel function is a non-parametric estimation approach of the probability density function of a random variable. Villa (2012) uses a default estimator with an underlying epanechnikov kernel smoothing function and 0.06 bandwidth h_n such that for mean μand indicator function $\mathbf{1}\{\dots\}$ defined on the covariate set X :

$$K(\mu) = \frac{3}{4}(1 - \mu^2)\mathbf{1}_{\{|\mu| \leq 1\}.}$$

Recall that I assume that the heterogeneity of the soil type and underlying hydrology are already accounted for in the field (water right) fixed effect such that I do not include soil or hydrological covariates as these are variables that remain constant across time. However, variability in soils related to soil moisture content does change over time such that I assume that this variability is embedded in the weather variables of precipitation and evapotranspiration. I base the kernel propensity score of similar irrigators based on weather, irrigation technology and crop type. The results are summarized in Table 6.

Although I find that failing to account for the differences among irrigators that varies through time generates different estimates from our preferred model estimates, I find the majority of the response at the total intensive margin (28.1%) compared to the total extensive margin (-2.9%) with an overall water use reduction of -29.8% which is consistent with our previous descriptive interpretations. However, only the response at the intensive margin is statistically significant. I additionally explore the importance of the farmer-time effect and the weather controls (Table 7).

Table 6: Difference-In-Difference Kernel Propensity Score Matching Estimator Marginal Effects

Variable(s)		5 Mile	LEMA	LEMA Effect
Total Effect	Pre-Policy	7.351	7.434	
	Post-Policy	7.411	7.141	
	Difference	0.083**	-0.271**	-0.298**
		(0.064)	(0.056)	(0.081)
Extensive	Pre-Policy	4.888	4.887	
	Post-Policy	4.902	4.872	
	Difference	-0.030	-0.030	-0.029
		(0.032)	(0.036)	(0.015)
Intensive	Pre-Policy	2.463	2.547	
	Post-Policy	2.515	2.269	
	Difference	0.084**	-0.246**	-0.281**
		(0.028)	(0.033)	(0.027)

Notes: * and ** denote significance at the 5% and 1% levels. LEMA effect estimates adjusted for log-linear correction.

If I assume that unobserved differences across irrigators are constant across time, then the addition of a farmer specific fixed effect would suffice. However, in our fixed effects model this is already accounted for in the water right fixed effect α . I suggest the need to additionally account for unobserved differences across irrigators that are varying through time, that is, to account for variability due to skills, experience, management practices, finances, etc.

I evaluate the importance of inclusion of these additional model parameters and note the changes to the coefficient estimates with varying controls in Table 6 below. Column (1) indicates the D-I-D estimates that only include a water right-specific (α_i) and time-specific (δ_t) fixed effect without controls. Column (2) additionally includes a set of weather (X_{it}) controls that vary across water rights and time. Column (3) includes the set of farmer-time effect (λ_{ft}) but removes the weather controls. Column (4) represents the preferred model with both the farmer-time effect and weather controls.

Table 7: Comparison of Marginal Effects Estimates with Varying Controls

	Log Total Applied Inches (Total Effect)			
Variable/Statistics	(1)	(2)	(3)	(4)
LEMA policy effect	-0.330**	-0.312**	-0.251**	-0.242**
	(0.027)	(0.026)	(0.046)	(0.034)
Weather				
Precipitation		-0.039**		-0.025**
		(0.006)		(0.012)
Evapotranspiration		0.056		-0.035
		(0.047)		(0.082)
Water Right Fixed	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Farmer-time Fixed	No	No	Yes	Yes
N	2817	2817	2817	2817
R^2	0.0708	0.0774	0.1848	0.1846

Note: Parentheses denote robust clustered (well-level) std. errors. $*$ and $**$ denote significance at the 5% and 1% levels. Water right, Time and Farmer-time specific estimates were removed for conciseness (N>1000). LEMA effect estimates adjusted for log-linear correction.

I find confirmation that adding in the weather controls does little to the estimates by comparing columns (1) and (2). However, by comparing columns (2) and (3) the addition of the farmer-time effect changes the impact more. This lends evidence for the preferred specification such that removing the farmer-time effect and weather controls will inflate the causal estimate of the LEMA effect. Although the weather controls are of no dire consequence to this study, this is likely due to the fact that the policy area is small and little variability exists in the weather data.

6.2.5 Falsifications Tests

I want to alleviate any concerns that the control group might have selection bias or rather, is not indeed a valid counterfactual such that LEMA farmers would have acted as the control had they not been under the LEMA policy. I compare the 5 Mile control group to a 10 mile control group and run the same fixed effects model of marginal elasticities as a falsification test. There is no statistical difference between the two groups, and as such I have confidence that no selection bias is in the chosen 5 mile boundary as the basis of comparison for the LEMA (Table 8).

Table 8: Falsification Test: Measuring the Difference Between a 5 Mile and a 10 Mile Counterfactual Control Group

	Total Effect	***Extensive***	***Intensive***	
Variable/Statistics		Total	Total	Direct
LEMA policy effect	0.028	0.002	0.028	0.033
	(0.103)	(0.051)	(0.109)	(0.107)
Cropping Type				
Alfalfa				-0.112
				(0.116)
Corn				-0.005
				(0.087)
Sorghum				0.159
				(0.189)
Soybean				-0.142
				(0.091)
Wheat				-0.205
				(0.135)
Weather				
Precipitation (inches)	-0.014	0.008	-0.022	-0.018
	(0.014)	(0.008)	(0.015)	(0.015)
Evapotranspiration	-0.060	0.198	-0.138	-0.194
	(0.238)	(0.147)	(0.249)	(0.259)
N	1443	1443	1443	1441
R^2	0.1791	0.0161	0.2814	0.2908

Note: The dependent variable is given by the column heading. Parentheses denote robust clustered (water right level) std. errors. $*$ and $**$ denote significance at the 5% and 1% levels. Farmer-Time specific estimates were removed for conciseness. LEMA effect estimates adjusted for log-linear correction only.

I also construct a false timing policy to see if there is any statistical significance from our fixed effects model framework. I restrict the data to 2009 through 2012 (prior to the LEMA) and create a false policy effect in 2010. I run my previous regressions for decomposed marginal estimates and find all marginal effects to be small with no statistical significance (Table 9). This indicates the effect is not statistically different from zero and we can infer a non-effect from the ficticious 2010 policy. This establishes our statistical importance of the LEMA policy effect.

Table 9: Falsification Test: The Marginal Effects of a False 2010 Time Signal

	Total Effect	***Extensive***	***Intensive***	
Variable/Statistics		Total	Total	Direct
FALSE policy effect	-0.052	-0.001	-0.052	-0.040
	(0.037)	(0.015)	(0.038)	(0.107)
Cropping Type				
Alfalfa				-0.083
				(0.124)
Corn				0.105
				(0.066)
Sorghum				0.077
				(0.104)
Soybean				0.002
				(0.091)
Wheat				-0.421**
				(0.158)
Weather				
Precipitation (inches)	-0.010	0.004	-0.014	-0.018
	(0.013)	(0.005)	(0.013)	(0.014)
Evapotranspiration	-0.076	0.004	-0.014	-0.018
	(0.013)	(0.005)	(0.078)	(0.074)
N	1889	1889	1889	1889
R^2	0.8063	0.3405	0.7754	0.7880

Note: The dependent variable is given by the column heading. Parentheses denote robust clustered (water right level) std. errors. $*$ and $**$ denote significance at the 5% and 1% levels. Farmer-Time specific estimates were removed for conciseness. LEMA effect estimates adjusted for log-linear correction only.

The fixed effects model is an important framework for identifying the causal parameter of interest and provides insight into how irrigators chose to change their water use behavior at the extensive and intensive margins. However, I additionally want to further describe the heterogeneity in water use decisions among the LEMA irrigators. Although this portion of the study is just a pre/post policy comparison of changes inside the LEMA and therefore cannot be identified as occurring due to the water policy (i.e. because there is no counterfactual scenario), it is still useful to extend our analysis of how irrigators chose to change their water use behavior into more detailed descriptive statistics

6.3 Heterogeneous Response of LEMA Irrigators

I decompose the intensive response to determine reductions as either changes in applied inches/acre or irrigators modifying the crop type planted, however, this method cannot be applied at the extensive margin. I do wish to provide further description of this response based on varying characteristics among the irrigators.

I am first interested in the proportion of water right holders that chose to reduce irrigated acreage because I found that there was very little average response at the total extensive margin. Out of 184 unique LEMA water rights, the majority of LEMA water right holders (99) made no changes to irrigated acreage. However, of the LEMA irrigators that chose to modify their acreage, 28 water rights had reductions up to 10 acres and 18 water rights had expand up to 10 acres, followed by various changes in irrigated acreage in much smaller proportions among remaining water right holders (Figure 23).

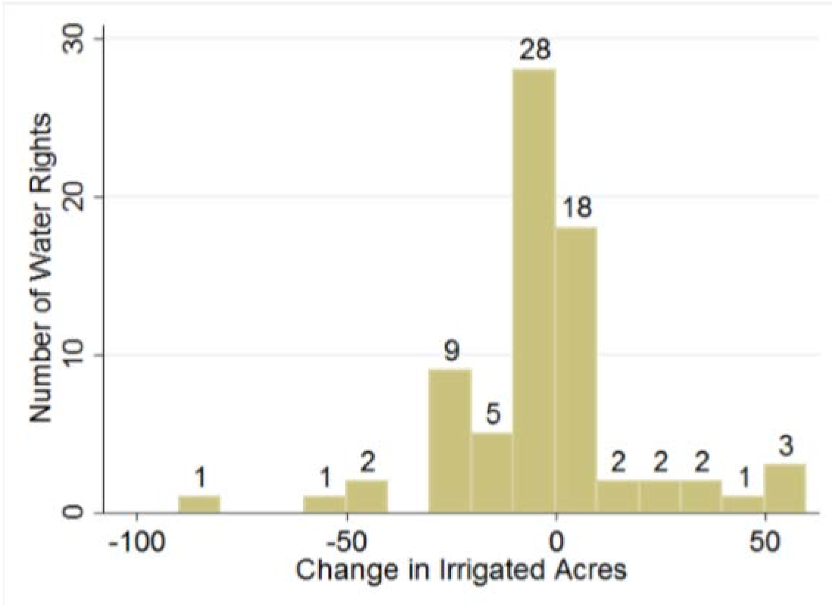


Figure 23: Distribution of Water Rights that Made Changes to Total Irrigated Acres

I am also interested to see the variability in response to changes in irrigated acres among the 180 LEMA water rights holders who have a pivot-drop system (87%) as indicated in the summary statistics. Many LEMA water rights (101) that have a pivot-drop system maintained the same level of irrigated acreage. Of those water rights associated with pivot drop systems and changes to irrigated acreage, the majority of irrigators (24) chose to reduce up to 10 acres and 13 irrigators chose to expand up to 10 acres, followed again by various changes in irrigated acreage in much smaller proportions among the remaining water right holders (Figure 24).

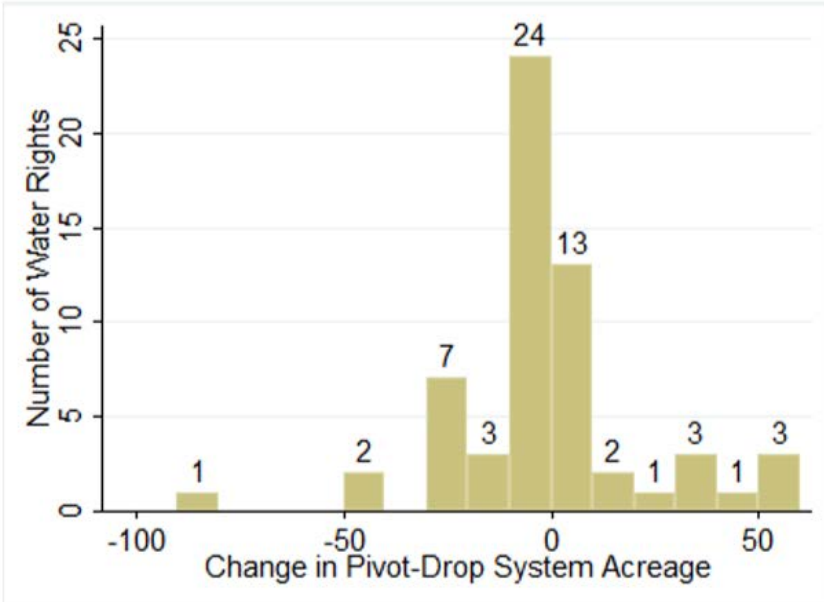


Figure 24: Distribution of Irrigators with Pivot-Drop Systems that Made Changes to Total Irrigated Acres

I additionally consider the heterogeneous response as it relates to crop specific and farmer-specific responses. Of the 184 water rights, all water rights associated with alfalfa, wheat, and other crops made no changes to irrigated acreage after the LEMA went into effect. For the water rights that were associated with changes to irrigated acreage, I find the majority of reductions (157) to come from corn with 13 water rights reducing up to 10 acres, followed by 11 water rights expanding up to 10 acres (Figure 25). Soybean farmers had primarily 30-50 acre reductions with only 1 farmer choosing to expand up to 10 acres (Figure 26). Additionally, I find that all sorghum water rights expanded irrigated acreage between 80-140 acres where previously there had not been acreage dedicated to this crop (Figure 27).

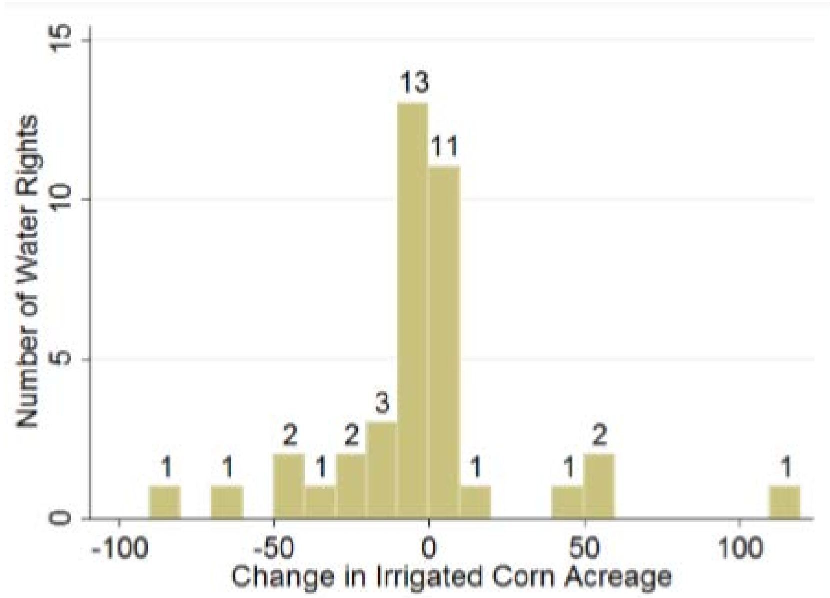


Figure 25: Change in Irrigated Corn Acres (By Water Rights)

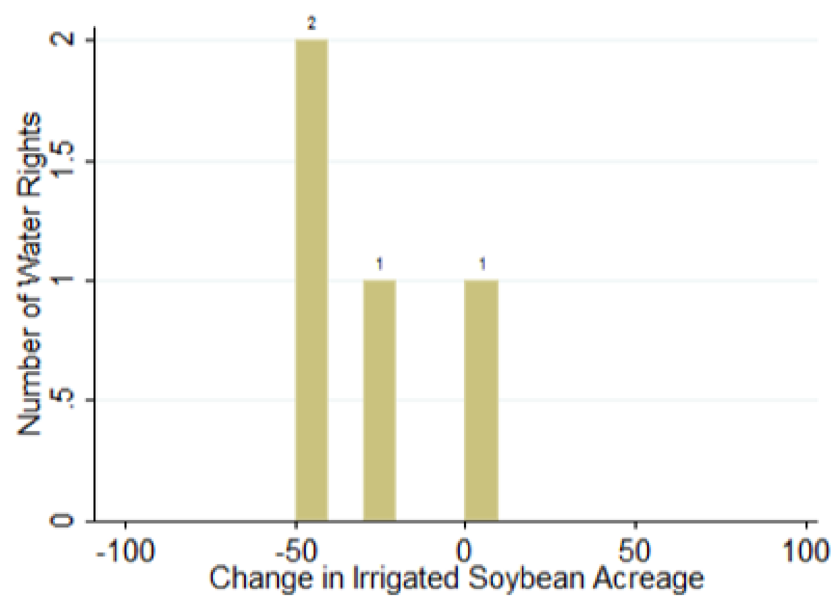


Figure 26: Change in Irrigated Soybean Acres (By Water Rights)

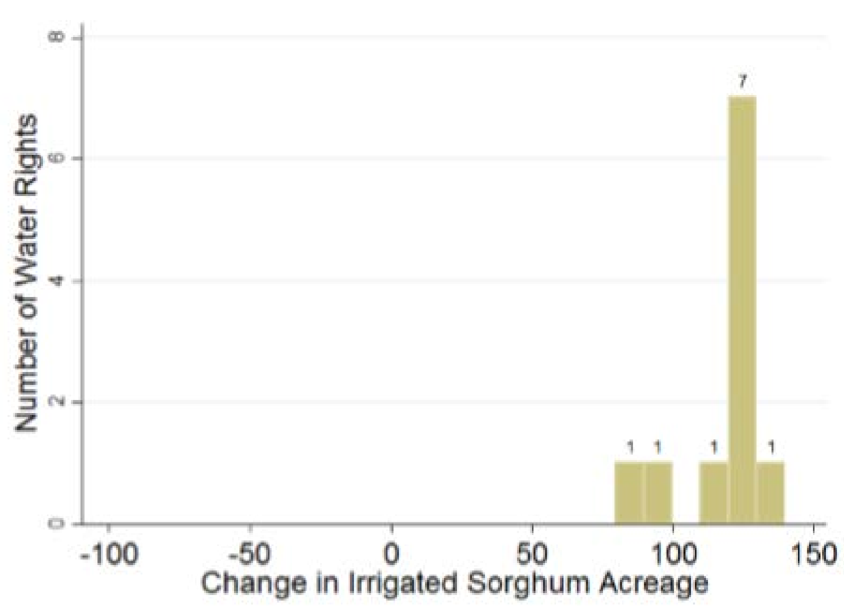


Figure 27: Change in Irrigated Sorghum Acres (By Water Rights)

6.4 Field and Farmer Specific Characteristics

Because irrigators can have multiple water rights and multiple wells, I wish to explore the heterogeneity as it relates to well ownership and irrigated acreage among irrigators. Although we previously selected our unique identifier as the water right itself it is now necessary to use the irrigator ID and well ID as the unique identifier. This is because irrigators may have multiple water rights on the same field or a water right may be associated with multiple wells that are irrigating different crops.

Additionally, because of the nature of water rights and land values, the same well cannot be attached to multiple water rights. Because I want to uncover the heterogeneity of the response I do not want to aggregate these descriptive statistics to the same water right ID, but rather maintain the disaggregated information in the data. Figure 28 indicates that the majority of irrigators inside the LEMA had access to just one (38) well followed by irrigators who maintained 2 or more wells.

Although many corn farmers (14) made no change to irrigated acreage, the majority of corn farmers (17) reduced irrigated acreage up to 10 acres (Figure 29). Furthermore, all sorghum acreage was expanded new post policy acreage between 100-130 irrigated acres. For soybean farmers, although 5 irrigators made no change to soybean acreage, I find a split between farmers who chose to expand (3) or reduce (3) acres irrigated (Figure 30). As a result, we can see more clearly how the small reductions of the majority of corn farmers did little to offset the larger expansions in soybean and sorghum (Figure 31) of a small number of farmers and resulted in little total extensive marginal response.

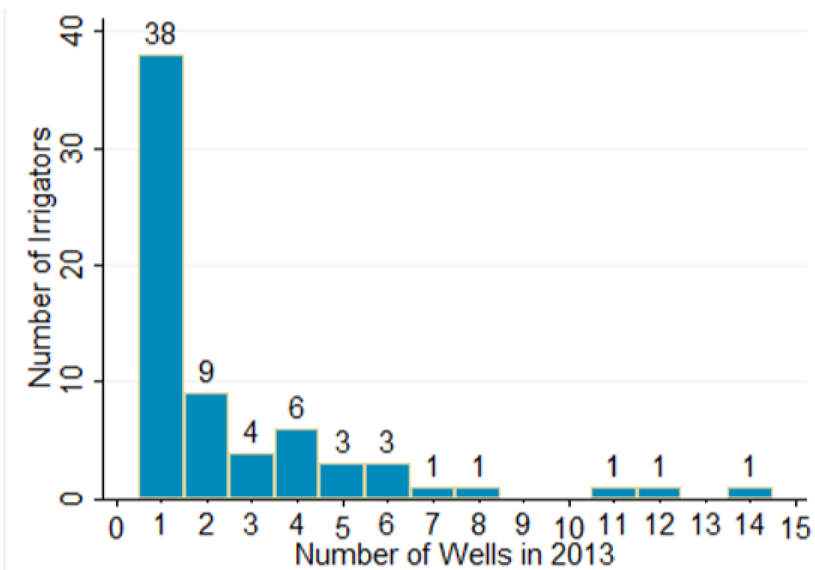


Figure 28: Distribution of Well Ownership (per Farmer)

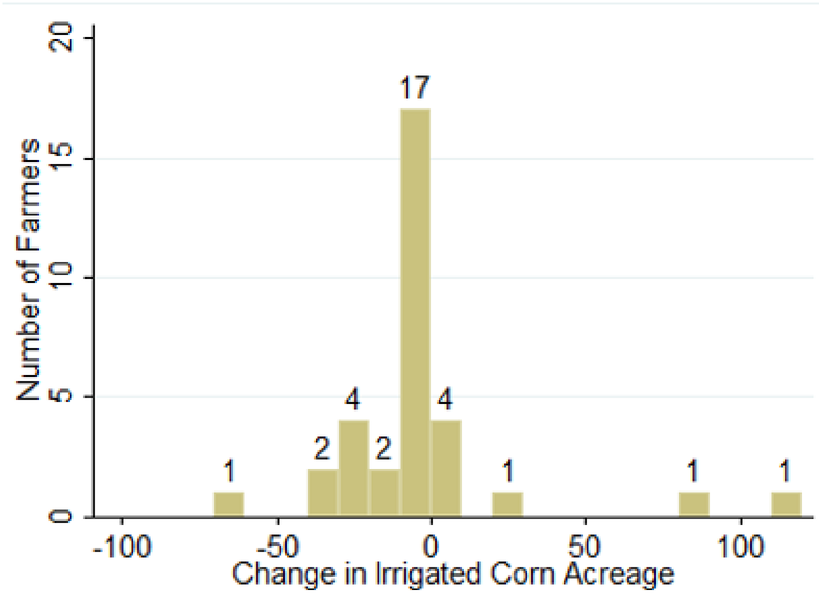


Figure 29: Change in Irrigated Corn Acres (per Farmer)

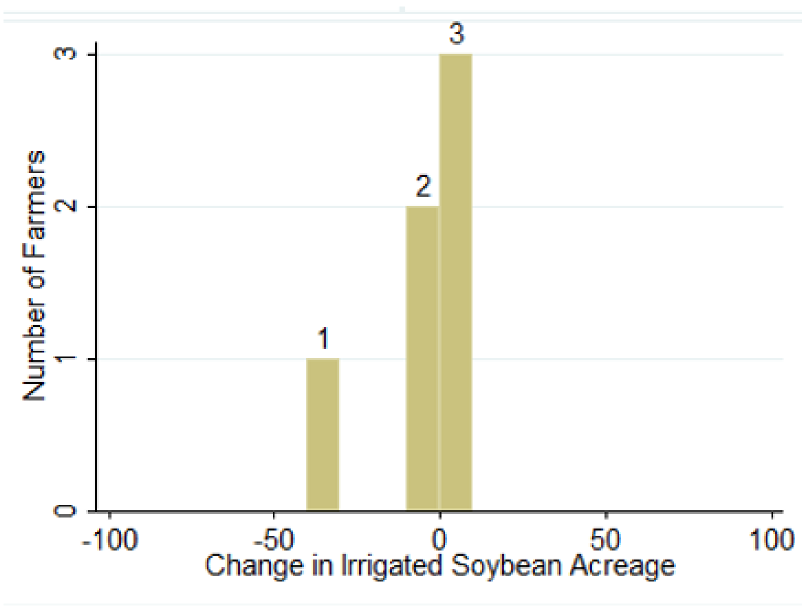


Figure 30: Change in Irrigated Soybean Acres (per Farmer)

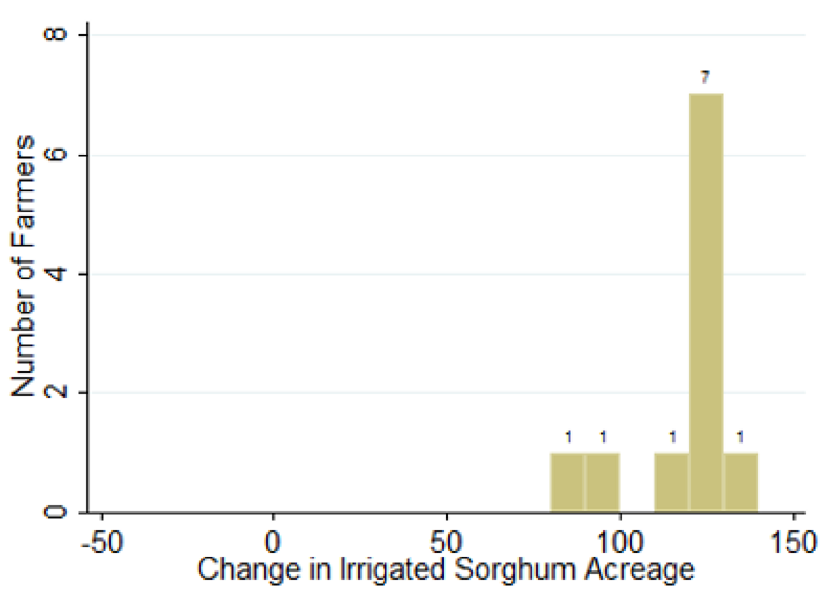


Figure 31: Change in Irrigated Sorghum Acres (per Farmer)

6.5 Large Irrigators

I previously found that 49 irrigators chose to make no changes to irrigated acreage. I also indicated that there was no evidence to suggest that irrigators inside the LEMA who managed more than one well would increase applied water use. In Figure 32 we see how the majority of irrigators with only one well who managed the same crop across all years also chose to expand acreage up to 10 acres but very few irrigators with multiple wells increased irrigated acres beyond that lending further evidence that well flexibility doesn’t allow for disproportionate water restrictions.

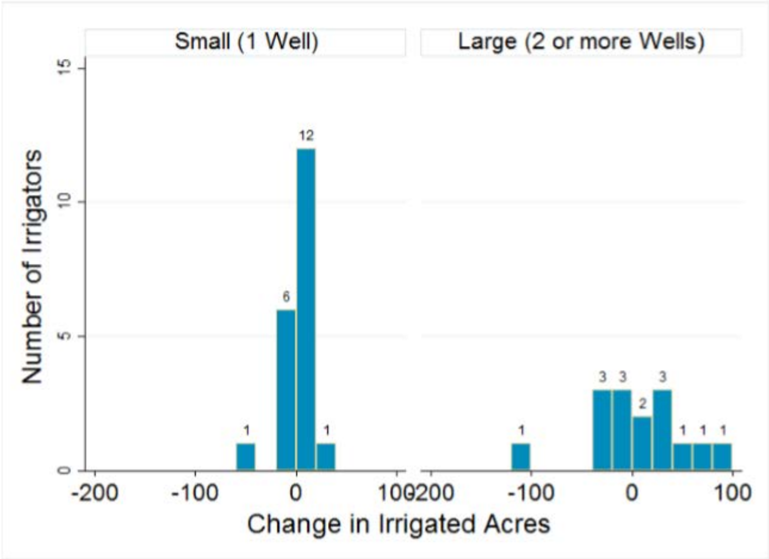


Figure 32: Disproportionate Water Use Among Farmers

I also restrict large irrigators of the same crop using a pivot-drop irrigation system and find that the majority of these water right holders reduced acreage. This provides further evidence that the majority of the response was related to decisions of crop type (more water-intensive varieties) rather than more efficient technologies are impacting the extensive marginal effects (Figure 33). This is consistent with the findings of Hornbeck and Keskin (2014) in that irrigated land use has adjusted toward water-intensive crops.

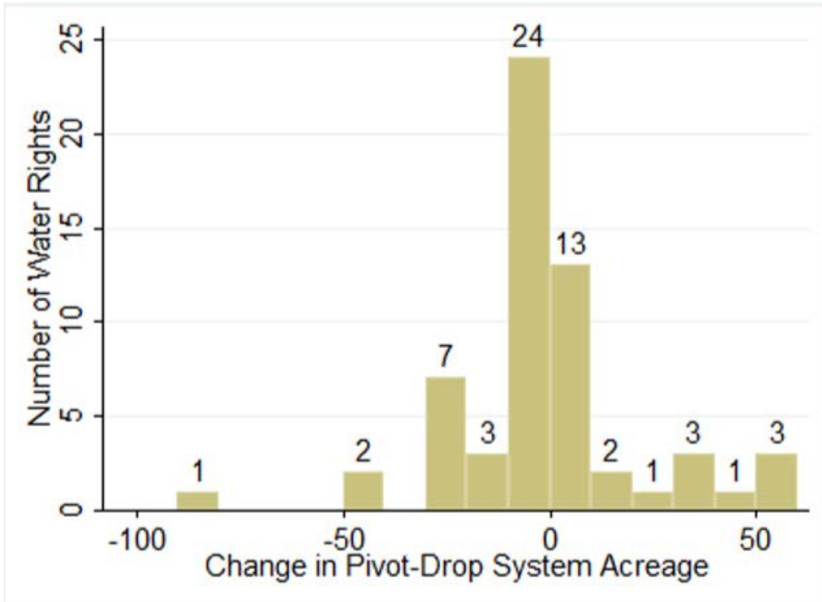


Figure 33: Disproportionate Water Use Among Pivot System Farmers

Chapter 7 - Results: Changes in Cropping Patterns and Input Expenditures

Given the LEMA policy significantly impacted planted acres, there could be substantial impacts on seed and chemical expenditures. The results in Table 3 from Chapter 6 indicate that farmers inside the LEMA responded primarily at the intensive margin by reducing their intensity of applied inches per acre. This result is consistent with numerical simulations of Foster et al. (2014) and Wibowo et al. (2017) that indicate that irrigators respond to reduced water availability by first reducing water use at the intensive margin. It is important to note, however, that large restrictions could in turn cause farmers to have a greater response at the extensive margin whereby reducing crop acreage.

Nevertheless, even the relatively small changes to cropping patterns have impacts on other agricultural sectors. Using Kansas State University's crop budgets for Northwestern Kansas, I estimate the effect the LEMA could have on expenditures for corn, soybean, sorghum, and wheat. The subsequent effects of irrigation on other agricultural sectors have also received substantial interest (e.g., Hornbeck and Keskin, 2015). While I do not have actual input data, I can approximate the effects on inputs by using the estimates of changes in cropping patterns and information obtained from Kansas State University irrigated crop budgets. Table 10 shows the irrigated input expenditures for each crop. I use the average of sorghum and wheat for the crop category identified as "other" and assume the input of alfalfa to be similar of "other crops" and apply those input expenditure estimates.

Table 10: Input Expenditure by Crop Type

Expenditure per Acre					
Input	Corn	Soybean	Sorghum	Wheat	Other
Fertilizer	$84.18	$18.83	$60.93	$38.74	$49.84
Herbicide	$48.95	$34.95	$6.31	$41.25	$23.78
Insecticide	$14.57	-	-	-	-
Seed	$113.92	$55.50	$18.00	$14.92	$16.46

Note: "Other" crop expenditures are calculated as the average of sorghum and wheat expenditures. Alfalfa expenditures are assumed to be the same as "Other" expenditures.

Unfortunately, I also do not know the exact allocation of crops used in the category identified as "multiple crops", however, I can use a general allocation as follows: 50% corn, 20% soybeans, 10% wheat, 10% sorghum, 5% alfalfa and 5% other. I can then add this allocation to the individual crop shares to determine an overall crop share estimate (Table 11). I then further calculate the change in expenditures for fertilizer, herbicide, insecticide, and seed using the pre-treatment average share of each crop from Table 10 and the change in the share of each crop due to the LEMA effect using the preferred fixed effects model specification column (1) from Tables 12 and 13 to get the resulting input expenditure effects (Table 14).

Table 11:Pre LEMA Average Share of Crop Irrigated Acres

Pre Policy Share of Acres inside LEMA Boundary							
	Corn	Soybean	Sorghum	Wheat	Alfalfa	Other	Multi
Mean	0.683	0.182	0.002	0.022	0.013	0.008	0.088
% of Multi	0.5	0.2	0.1	0.1	0.05	0.05	
MultiShare	0.044	0.018	0.0088	0.0088	0.0044	0.0044	
Total Share	0.73	0.20	0.01	0.03	0.02	0.02	

Table 12: LEMA Effect on Share of Corn, Soybean and Sorghum Irrigated Acres

Variable/Statistic	***Change in Share Acres***	
Corn	(1)	(2)
LEMA Effect	-0.125*	-0.075*
	(0.0450)	(0.030)
Weather		
Precipitation (inches)	-0.004	-0.013*
	(0.015)	(0.006)
Evapotranspiration	0.139	0.118*
	(0.137)	(0.044)
N	2819	2819
R^2	0.5018	0.0130
Soybean		
LEMA Effect	0.005	0.009
	(0.047)	(0.022)
Weather		
Precipitation (inches)	0.007	0.007
	(0.013)	(0.005)
Evapotranspiration	0.059	-0.060
	(0.122)	(0.033)
N	2819	2819
R^2	0.4761	0.0120
Sorghum		
LEMA Effect	0.081**	0.415**
	(0.028)	(0.014)
Weather		
Precipitation (inches)	-0.002	0.005
	(0.004)	(0.002)
Evapotranspiration	-0.019	-0.033
	(0.026)	(0.014)
N	2819	2819
R^2	0.5185	0.0312
Water Right Fixed	Yes	Yes
Time Fixed Effect	Yes	Yes
Farmer-time Fixed	Yes	No

Note: Parentheses denote robust clustered (water right level) std. errors. ∗ and ∗∗ denote significance at the 5% and 1% levels. Farmer-Time specific estimates were removed for conciseness.

Table 13: LEMA Effect on Share of Wheat, Alfalfa and Other Irrigated Acres

Variable/Statistic	***Change in Share Acres***	
Wheat	(1)	(2)
LEMA Effect	0.028	0.007
	(0.031)	(0.147)
Weather		
Precipitation (inches)	-0.004	-0.002
	(0.006)	(0.003)
Evapotranspiration	-0.002	0.012
	(0.037)	(0.019)
N	2819	2819
R^2	0.5895	(0.051)
Alfalfa		
LEMA Effect	0.006	-0.004
	(0.010)	(0.006)
Weather		
Precipitation (inches)	-0.002	0.002
	(0.002)	(0.002)
Evapotranspiration	0.146	-0.011
	(0.013)	(0.009)
N	2819	2819
R^2	0.5432	0.0065
Other		
LEMA Effect	0.001	0.006
	(0.009)	(0.008)
Weather		
Precipitation (inches)	0.002	0.001
	(0.004)	(0.002)
Evapotranspiration	0.012	0.002
	(0.017)	(0.013)
N	2819	2819
R^2	0.4377	0.0016
Water Right Fixed	Yes	Yes
Time Fixed Effect	Yes	Yes
Farmer-time Fixed	Yes	No

Note: Parentheses denote robust clustered (water right level) std. errors. $*$ and $**$ denote significance at the 5% and 1% levels. Farmer-Time specific estimates were removed for conciseness.

Table 14: LEMA Effect on Crop Specific Input Expenditures

	Pre Policy	LEMA Effect	Post Policy	% Change
Fertilizer				
Corn	$61.45	-$10.52	$50.93	-17%
Soybean	$3.77	$0.09	$3.86	2%
Sorghum	$0.61	$4.94	$5.55	809%
Wheat	$1.16	$1.9	$3.06	469%
Alfalfa	$1.00	$0.30	$1.30	30%
Other	$1.00	$0.05	$1.05	2%
	$79.94		**$65.75**	**-18%**
Herbicide				
Corn	$35.73	-$6.12	$29.61	-17%
Soybean	$6.99	$0.17	$7.16	2%
Sorghum	$3.71	$0.51	$4.22	14%
Wheat	$0.69	$1.16	$1.85	168%
Alfalfa	$11.89	$0.14	$12.03	1%
Other	$11.89	$0.02	$11.91	2%
	$70.90		**$66.78**	**-6%**
Insecticide				
Corn	$10.57	-$1.82	**$8.75**	-17%
Soybean	-	-		0%
Sorghum	-	-		0%
Wheat	-	-		0%
Alfalfa	-	-		0%
Other	-	-		0%
	$10.57	**-$1.82**	**$8.75**	**-17%**
Seed				
Corn	$83.16	-$14.24	$68.92	-17%
Soybean	$11.10	$0.28	$11.38	2%
Sorghum	$1.34	$1.46	$2.80	109%
Wheat	$1.98	$0.42	$2.40	21%
Alfalfa	$0.82	$0.10	$0.92	12%
Other	$0.82	$0.02	$0.80	2%
	$99.22		**$88.22**	**-11%**
Total	**$260.63**		**220.75**	**-15%**

The effect of the LEMA resulted primarily in reductions to corn (12.5%), however, corn has relatively higher input expenditures compared to soybean, wheat, sorghum and alfalfa. Because of this impacts to input expenditures will be largely driven by the subsequent impacts to changes in corn acreage. For farmers within the LEMA, overall seed and chemical expenditures dropped significantly, especially for corn. The overall reduction was roughly 15 percent (Table 14). Although many individual crops, such as sorghum and wheat, had an increase in overall expenditures, the relative share and associated costs were dominated by the reductions in corn expenditures. Herbicide and insecticide expenditures declined by 6 and 17 percent, respectively. Seed expenditures dropped by 11 percent and the largest reductions occurred for fertilizer expenditures at 17 percent. I discussed in Chapter 6 that the LEMA effect had a relatively small impact on water savings due to changes in cropping patterns, however, we can see that the subsequent changes on chemical and seed expenditures was quite large. These results have important implications for the impact of the LEMA on agribusiness firms that sell inputs to farmers.

Chapter 8 - Results: Changes in Crop Yields

8.1 D-I-D Model and Visual Analysis

In total there are 1,434 observations for corn and only 189 observations for soybeans as there are relatively few water rights subject to the LEMA that are planted solely to soybeans. I first estimate the effects of water use intensity on yields from the LEMA using a standard D-I-D framework. The D-I-D model accounts for unobserved heterogeneity of water rights that are constant over time (i.e. water right-specific differences) and also accounts for the annual heterogeneity that is constant across fields (i.e. crop, energy, and other input prices). The results in Table 15 indicate a 14.16% reduction in response to the LEMA for corn and a reduction of 5.57% for soybeans. These D-I-D results are visualized in Figures 34 and 35.

Table 15: Difference-in-Difference for Yields

	Intensive Margin		
	LEMA	5 Mile	Dif
Corn			
Pre	200.68	201.51	-0.83
	(1.456)	(1.286)	
Post	181.42	194.75	-13.33
	(1.484)	(1.394)	
	19.26	6.76	-14.16
Soybean	19.26	6.76	-14.16
Pre	64.24	61.67	2.57
	(0.995)	(1.134)	
Post	58.82	61.82	-3.00
	(1.019)	(1.600)	
	5.42	-0.15	-5.57

Note: Parentheses denote std. errors. $*$ and $**$ denote significance at the 5% and 1% levels.

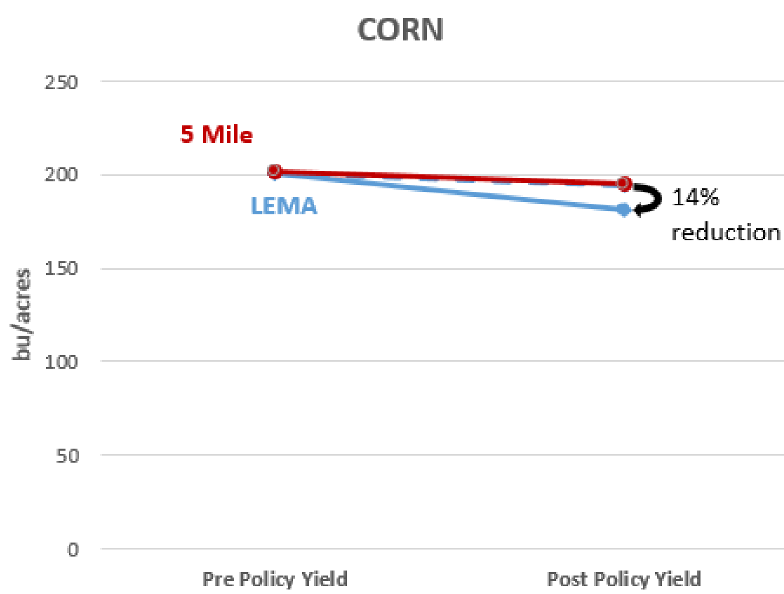


Figure 34: Difference-In-Difference Results for Corn Yields

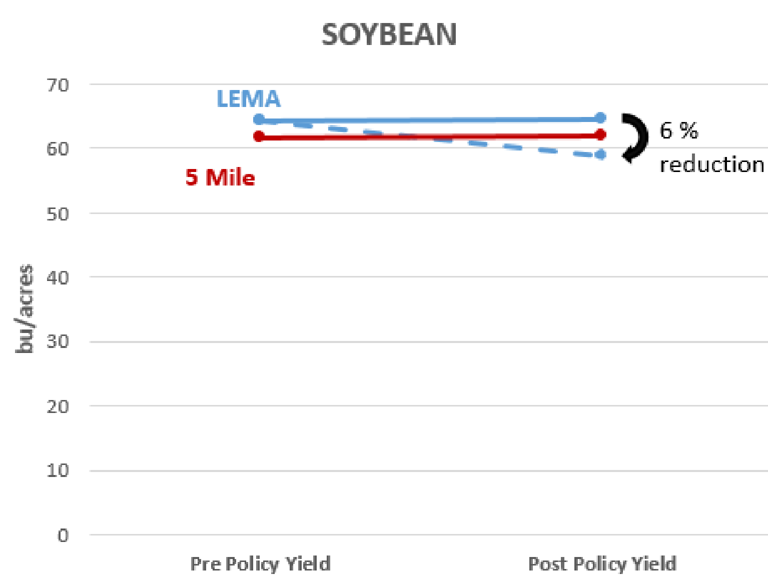


Figure 35: Difference-In-Difference Results for Soybean Yields

8.2 Econometric Results

Additionally, it is important to consider the need for other control variables such as the farmer-time fixed effects that was used in the preferred model when investigating the effects at the intensive and extensive margins of water use. It is worth noting, however, that in the case of soybeans I have a large number of right hand side variables compared to a relatively small number of observations that make this unfeasible.

Table 16 shows the D-I-D regression results. For corn, I find that both models (1) and (2) report statistically significant results at the 1% confidence interval, however, if we exclude the farmer-time fixed effects (2) we estimate a smaller effect of the LEMA on yields by 1.87%, such that the estimated effect on corn yield is a reduction of 8.37%. For soybeans, I find that when I include the farmer-time fixed effects, the model produces an unlikely result (4). The result for the model omitting the farmer-time fixed effects indicates a smaller but statistically significant reduction for soybean yield of 4.18% in response to the LEMA (4).

Although I cannot quantify the exact short-run welfare impacts from the LEMA without observed yield data or production cost data, I can use this information combined with average price data to discuss the further implications of farmers' welfare. USDA Quickstats (2017) indicates estimates of average bushels per acre for corn in neighboring Thomas County, KS to be 200.9 in 2014 and 192.5 in 2011. USDA indicates soybean yield to be 59 bushels per acre in both 2006 and 2007. I find similar estimates in average predicted yields for the sample area for corn and soybean of 197.76 and 62.22, respectfully. Schnitkey and Hubbs (2015) indicate that a price for corn of $3.50 and $9.75 for soybean for the 2018-2019 marketing year to be realistic estimates. This indicates average revenues per acre for corn at $692.16 and soybean at $606.65. Combining this with the estimates produced from Table 16 we can estimate the subsequent reductions on crop revenues to be -$57.93 per acre for corn and -$25.36 per acre for soybean. The impacts on profits might not have been as large if producers chose to adjust other costs of production (e.g. applied less additional inputs.)

Table 16: Comparison of Models of Effects of Yields

	Log Yield			
Variable/Statistics	Corn		Soybean	
	(1)	(2)	(3)	(4)
LEMA policy effect	-10.24**	-8.37**	- 4.18*	47.72
	(2.299)	(0.980)	(0.603)	(4.217)
Weather				
Precipitation (inches)	0.03**	0.01**	0.73	0.02
	(0.008)	(0.031)	-	(0.256)
Evapotranspiration	-0.01	0.03	3.92	0.06
	(0.044)	(0.017)	-	(0.056)
Water Right Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Farmer-time Fixed Effect	No	Yes	No	Yes
N	1430	1430	187	187
R^2	0.0708	0.0774	0.1848	0.1846

Note: Parentheses denote robust clustered (well-level) std. errors. $*$ and $**$ denote significance at the 5% and 1% levels. Water right, Time and Farmer-time specific estimates were removed for conciseness (N>1000). LEMA effect estimates adjusted for log-linear correction.

Chapter 9 - Conclusion

This research uses an econometric approach to uncover the effects on water use and crop type from the collective action water management plan identified as the Sheridan 6 LEMA. Many agricultural businesses will also be impacted by changes in these on-farm decisions through changes to additional input markets such as fertilizer use, seed and grain flows. The possibility of new water restricted areas has increasingly become a topic for producers and agribusinesses and collective action management plans are a potential policy instrument to sustain the life of the High Plains Aquifer for generations to come with the recent implementation of two additional LEMAs: the district-wide GMD 4 and the Rattlesnake/Quivara management area.

There are some limitations to this research. I had limited observations for many crops apart from corn and soybean, the primary crops of the area, such that I could not estimate some crop specific yields in a meaningful way. Additionally, I did not know the exact proportion of acreage for farmers who implemented crop rotations or had acreage planted to multiple crops, as such I had to make assumptions on particular crop mixes to obtain results. I also did not have actual yield data and used simulated data such that it is possible that my yield curve is misspecified. Additionally, I used average pricing data such that I had to assume average prices to determine subsequent outcomes on farmers' welfare. It is also possible that irrigators could have made adjustments to minimize any yield losses. Additionally, this research only includes 2 years of post-policy data, which provides us with insight on the very short run decisions of the irrigators inside the LEMA, however, the policy directive is for 5 years. It would be important to run the same analysis in the future to capture the full effect of the policy. Importantly, farmers' decisions in the first four years could impact how much water they use in the final year. It is possible that water use in the last year may have increased compared to earlier years when farmers know how much allotment they have remaining, assuming they sufficiently reduced water use the prior four years.

Using a Difference-in-Differences (D-I-D) model I expose the causal effect of the LEMA policy on important farmer decisions relating to water use, yields and inputs. The more simplistic D-I-D framework allows us to estimate the before and after difference inside the LEMA and compare it to the before and after difference in the 5 mile buffer zone (control group) just outside the LEMA. This model is strict in its assumptions and I find evidence for an alternative regression model that controls for variability of each farmer across time by including the use of farmer-specific year fixed effects. This accounts for farmer variability not captured in the time fixed effect or the irrigator fixed effect relating to differences among irrigators such as skills, experience, management practices, and finances**.** Additionally, my proposed econometric framework allows for identification of the direct extensive (changes to irrigated acreage), direct intensive (changes to applied inches/acre) and indirect intensive (changes to crop type) margins of adjustment.

There are two main findings on the change in water use due to the LEMA. First, irrigators located inside the boundary of the LEMA made relatively small changes to total number of reduced irrigated acres and some irrigators moved from high water intensity crops to less water-intensive crops. Second, irrigators chose to apply significantly less water in inches per acre on corn and soybeans when compared to irrigators located in the control group which are the major crops grown in the region.

I find the greatest response to the LEMA at the intensive margin, implying that irrigators chose to reduce their applied water intensity by 21% with limited reductions in irrigated acreage (4%) indicating that the greater proportion of changes to applied inches of water per acre was not due to changes in cropping patterns and irrigation technology but due to reductions in applied water use intensities for the same crops.

Additionally, I evaluate concerns that irrigators with ownership of more than one well may lead to disproportionate water use restrictions due to the flexibility to move water rights between fields. I find no evidence that increased well ownership leads to increased water use and impacts smaller farms in greater proportion. In general, the collective action management plan was able to reduce water use overall having a positive impact on the aquifer and irrigators were able to reduce their water use intensity by a larger margin than reductions in irrigated acreage to comply with the provisions.

The impact of the LEMA significantly impacted producers choices on how much water to use and the crops raised. Fewer irrigated acres were planted to corn with the primary switch being to sorghum and soybeans. These changes have an impact on the crop input markets such as herbicides, pesticides, fertilizer and seed.

Although reductions in water use will slow the depletion of the aquifer, many additional agricultural businesses will be directly impacted by changes in water use decisions. My results indicate reductions to both corn (-8.37%) and soybean yields (-4.18%) as a direct effect of the LEMA. This has subsequent impacts to many businesses that could be impacted by changes in these on-farm decisions and additionally has important implications for the entire agricultural sector.

Not only does water use have a direct relationship with weather and climate variation, it also has a relationship to other on-farm production decisions including seed, herbicide and fertilizer use. The reduction in water use in the Sheridan County LEMA was estimated to reduce crop input expenditures of herbicides, pesticides, fertilizer and seed by roughly 15%. Although there were increases in many individual crop input expenditures, the relative share and associated costs were outshadowed by the reductions in corn expenditures. On the other hand, reduced groundwater depletion means that there will likely be more seed and chemical purchases in the future by extending the life of the aquifer. Producers have also made changes to irrigated acreage and have opted to switch crops for less water-intensive varieties although these changes were not the predominant factor.

The results from this study will prove useful to identify how irrigators adapted to the water policy restriction known as the LEMA and provide a framework that more accurately estimates the effect of a water policy. The possibility of new water restricted areas has increasingly become a topic for irrigators in Kansas. Reduced water use can extend the life of the aquifer but it is important to understand how farmers adapt and the subsequent impacts on farmers' profitability and input markets within the agricultural sector. Discussions for the implementation of new LEMAs are currently being conducted in other areas of Kansas and this analysis is beneficial to stakeholders in these areas and also has broader implications on water policy management initiatives across the US.

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MF 586 *Center-Pivot-Irrigated Soybean Cost-Return Budget in Western Kansas*
MF 582 *Center-Pivot-Irrigated Grain Sorghum Cost-Return Budget in Western Kansas*
MF 3148 *Wheat Cost-Return Budget in Northwest Kansas*

Appendix A - STATA CODE

```
*************************************************************************
*******
   ***Analysis of the Sheridan 6 LEMA inside/outside 5 Mile D-I-D
                              Model***
    ********Ch6: Extensive/Intensive marginal estimates of Water
                             Use*******
 **********************************************************************
 **********  clear
 set
 more
 off
 capt
 ure
 log
 clos
 e
 log using "..\Dissertation_Ch1_Code_draft - JEEM submission.txt", text
 replace

 ////////////////////////////////////////////////////////////////////////
 ////////

 ************************************************************************
 ********
                          //MODIFY KANSAS WATER USE DATA//
 ************************************************************************
 ********

 //Step 1: Clean Data for Combining Datasets

 *Import Water Use Data*
*Kansas Water Rights Information System Database (WRIS) after
*running the Water Group Tool in GIS

import delimited "..\dataAnalysis\Model and Output
files\ Kansas_PDIV_Reg_WaterGroup.csv"
duplicates report
duplicates report fpdiv_key
*duplicates list fpdiv_key
*list in 13937/13938
duplicates drop fpdiv_key, force
        *Bring in the actual reported Water Use Data
        merge 1:m fpdiv_key using
        "..\dataRaw\Water_Use_1991_2012.dta", ///  keep(match
        using) nogen

        *Note: wuadet_key needs to be unique to avoid double-
        counting duplicates report wuadet_key

        *remove unwanted data
        drop join_count target_fid wrf_active right_type vcnty_code ///
        wr_num wr_qual wrf_status source s_umw priority fpv_active
        twp_dir /// rng_dir dwr_id feet_north feet_west qual_four
        qual_three qual_two /// qual_one fo_num basin_num basin_name
        gwmd_num sua_code stream_num /// num_wells lot_number
        lot_qual1 lot_qual2 fpdiv_comm fpdiv_key wrf_key ///
        longitude latitude quant_id auth_quant add_quant quant_unit
        qstor_ind /// rate_id auth_rate add_rate rate_unit rstor_ind
```

```
            last_name first_name /// wris_date file_id name status fid_s
            shape_leng shape_area objectid /// wuacor_num wuafo_num
            wuaumwcode hours_pump pump_rate meter_qty /// meter_unit
            wur_code rpt_wright date_meas dpth_water dpth_well reel_num
            /// blip_num rpt_date chem_ind b_meter_rd e_meter_rd fid
            policy regulation /// grp_wr_cnt grp_pd_cnt

    *Update:(need to reformat to merge with new 2013 short data format)
    destring wuapers_id, generate (WUAPERS_ID) ignore(",")
    float drop wuapers_id
    destring wua_year, generate (WUA_YEAR) ignore(",")
    float drop wua_year
    destring wr_id, generate(WR_ID) ignore(",")
    float drop wr_id
    destring pdiv_id, generate(PDIV_ID) ignore(",")
    float drop pdiv_id
    destring acres_irr, generate(ACRES_IRR) ignore(",")
    float drop acres_irr
    destring af_used, generate(AF_USED) ignore(",") float
    drop af_used



     destring tacres_irr, generate(TACRES_IRR) ignore(",") float
     drop tacres_irr
     destring nacres_irr, generate(NACRES_IRR) ignore(",") float
     drop nacres_irr
     destring wr_group, generate(WR_GROUP) ignore(",") float
     drop wr_group

     destring crop_code, replace force
     sort crop_code
     gen CROP_CODE = crop_code
     drop crop_code

     generate TYPE_SYSTEM = system
     drop system
     generate UMW_CODE = umw_code
     drop umw_code

     rename twp TWP
     rename rng RNG
     rename sect SECT
     rename cnty_abrev CNTY_ABREV

     save "..\dataAnalysis\Model and Output files\
     Cleaned_MERGED_WATER_USE_Kansas_PDIV_Reg_W.dta", replace
     clear

*Bring in New 2013 Annual Reporting to match existing Data

     import excel "..\dataRaw\ORR_6440_Statewide_2013_Wuse_Data.xlsx", ///
     sheet("Sheet1") firstrow clear
     drop NEW_LONGITUDE NEW_LATITUDE
     drop if WUA_YEAR == .

     save "..\dataRaw\Cleaned_ORR_6440_Statewide_2013_Wuse_Data.dta", replace
     clear
     use "..\dataRaw\Cleaned_ORR_6440_Statewide_2013_Wuse_Data.dta", clear
```

```
**Bring in New 2014 Annual Reporting to match existing Data

        clear
        import excel "..\dataRaw\ORR_7202_2014_WUse_Data.xlsx", sheet("Sheet1") ///
        firstrow clear
        drop NEW_LONGITUDE NEW_LATITUDE
        drop if WUA_YEAR == .

        save "..\dataRaw\Cleaned_ORR_7202_2014_WUse_Data.dta", replace
        clear
        use "..\dataRaw\Cleaned_ORR_7202_2014_WUse_Data.dta", clear

        append using "..\dataRaw\Cleaned_ORR_6440_Statewide_2013_Wuse_Data.dta", ///
        force
        save "..\dataRaw\Cleaned_ORR_6440_Statewide_2013_2014_Wuse_Data.dta", ///
        replace
        append using "..\dataAnalysis\Model and Output files\
        Cleaned_MERGED_WATER_USE_Kansas_PDIV_Reg_W.dta", force

        *Generate Unique variable to sort on

        egen unique = concat (WR_ID PDIV_ID)
        destring unique, replace
        sort unique WUA_YEAR


        replace TWP = TWP[_n-1] if TWP >= . and unique[_n-1]== unique
        replace RNG = RNG[_n-1] if RNG >= . and unique[_n-1]== unique
        replace SECT = SECT[_n-1] if SECT >= . and unique[_n-1]== unique
        replace CNTY_ABREV = "." if missing(CNTY_ABREV)
        replace CNTY_ABREV = CNTY_ABREV[_n-1] if CNTY_ABREV >= "." and
        /// unique[_n-1]== unique
        replace TACRES_IRR = TACRES_IRR[_n-1] if TACRES_IRR >= . and
        /// unique[_n-1]== unique
        replace NACRES_IRR = NACRES_IRR[_n-1] if NACRES_IRR >= . and
        /// unique[_n-1]== unique
        replace WR_GROUP = WR_GROUP[_n-1] if WR_GROUP >= . and
        /// unique[_n-1]== unique
        replace WUAPERS_ID = WUAPERS_ID[_n-1] if WUAPERS_ID >= . and
        /// unique[_n-1]== unique

        *Final Kansas Water Use Dataset 1991-2014 (Dataset 1)

        *********************************************
        save "..\dataRaw\Cleaned_Water_Use_1991_2014_Export_Output.dta", replace
        clear
        *********************************************

*******************************************************************************
                         //MODIFY PRISM WEATHER DATA//
*******************************************************************************

//Step 2: Combine PRISM data 2009-2014 with Water Use Data

        *Modify PRISM data to match Water use data

        clear
        use "..\dataRaw\PLSS_PRISM_2009to14_CLEAN.dta"

        *Reformat to match variable names

        rename township TWP
        rename  range RNG
        rename isp_sectio SECT
        rename year WUA_YEAR
        rename month MONTH

        *Convert ppt from mm to inches

        replace ppt = ppt*(1/25.4)
```

```
        *Total avg annuals

        collapse (rawsum) ppt ET0, ///
                by (TWP RNG SECT WUA_YEAR)
                sum

        *Final Kansas Weather (monthly at TWP SECT RNG:3,801,096 obs) (Dataset 2)

        ********************************************
        save "..\dataRaw\PLSS_PRISM_2009to14_CLEAN_MONTHLY.dta" , replace
        clear
        ********************************************

*******************************************************************************
                         MERGE WATER and WEATHER DATA//
*******************************************************************************

//Step 3: Match to TWP SECT RNG in the LEMA water use dataset

*Begin with the Water use data (Dataset 1)

        use "..\dataRaw\Cleaned_Water_Use_1991_2014_Export_Output.dta"
        sort WR_ID WUA_YEAR
        sort SECT

*Bring in the Weather Data (Dataset 2)

        merge m:1 TWP RNG SECT WUA_YEAR using "..\dataRaw\
        PLSS_PRISM_2009to14_CLEAN_MONTHLY.dta", ///
        keep(match)
        drop _merge
        sort WR_ID WUA_YEAR

        *Kansas Water and Weather (Dataset 3)

        ********************************************
        save "..\Water_Use_WEATHER_WR.dta", replace
        clear
        ********************************************

//Step 3: Prepare Dataset to include variables for D-I-D LEMA and 5 Mile groups

*Add Dummy Variables for LEMA and 5 Mile to the original datasets

        *5 mile boundary data taken from ArcGIS Clipping Model**
        clear
        set more off
        import delimited "..\dataAnalysis\Model and Output files\5 Mile PDIV\
        Sheridan_LEMA_5Mile_Export_Output.csv"

        *check for unique observations

        duplicates report fpdiv_key
        duplicates drop fpdiv_key, force

        generate FIVE_MILE = 1
        generate LEMA = 0
        drop fid wrf_active right_type vcnty_code wr_num wr_qual wrf_status ///
        source s_umw priority fpv_active twp_dir rng_dir dwr_id feet_north ///
        feet_west qual_four qual_three qual_two qual_one fo_num basin_num ///
        basin_name gwmd_num cnty_abrev sua_code stream_num num_wells lot_number ///
        lot_qual1 lot_qual2 fpdiv_comm fpdiv_key wrf_key longitude latitude ///
        quant_id quant_unit qstor_ind rate_id rate_unit rstor_ind last_name ///
        first_name wris_date file_id auth_quant add_quant auth_rate add_rate ///
        grp_wr_cnt grp_pd_cnt

        *Reformat to match variable names

        generate WR_ID = wr_id
        drop wr_id
```

```
        generate PDIV_ID = pdiv_id
        drop pdiv_id
        generate UMW_CODE = umw_code
        drop umw_code
        generate SECT = sect
        drop sect
        generate TWP = twp
        drop twp
        generate RNG = rng
        drop rng

        *Restrict dataset to only irrigated users

        keep if UMW_CODE=="IRR"

        save "..\dataAnalysis\Model and Output files\5 Mile PDIV\
        Cleaned_Sheridan_LEMA_5Mile_Export_Output.dta",  replace
        clear

        *Bring in LEMA inside boundary taken from Water Office GIS files

        import excel "..\dataRaw\ORS_6440_SD_6_LEMA_WR_IDs_PDIV_IDs.xlsx", ///
        sheet("Sheet1") firstrow

        * Note: These are all irrigated water rights
        gen UMW_CODE="IRR"

        *check for unique observations
        duplicates report WR_ID PDIV_ID UMW_CODE
        generate FIVE_MILE = 0

        save "..\dataAnalysis\Model and Output files\Restricted PDIV\
        Cleaned_Sheridan_LEMA.dta", replace

        **Add back in the 5 Mile PDIV for the D-I-D Analysis

        append using "..\dataAnalysis\Model and Output files\5 Mile PDIV\
        Cleaned_Sheridan_LEMA_5Mile_Export_Output.dta", force

        *Reformat to match variable names
        generate TACRES_IRR = tacres_irr
        drop tacres_irr
        generate NACRES_IRR = nacres_irr
        drop nacres_irr
        generate WR_GROUP = wr_group
        drop wr_group

        * Note: Two observations are reported as both inside the LEMA and in the 5
        * mile boundary. Assume the KDA report on points of diversion inside the
        * LEMA is correct so drop if a duplicate and if FIVE_MILE==1

        duplicates report WR_ID PDIV_ID
        duplicates tag WR_ID PDIV_ID, gen(dup)
        list if dup==1
        drop if dup==1 and FIVE_MILE==1
        duplicates report WR_ID PDIV_ID
        drop dup

        *Final Kansas Water Rights dataset with D-I-D groups (Dataset 4)

        ********************************************
        save "..\dataAnalysis\Model and Output files\5 Mile PDIV\
        Cleaned_Sheridan_LEMA_5Mile_COMPLETE.dta", replace
        clear
        ********************************************

//Step 4: Merge the 2 datasets matching on WR_ID and PDIV_ID

        * Start with D-I-D groups (Dataset 4)
```

```
        use "..\dataAnalysis\Model and Output files\5 Mile PDIV\
        Cleaned_Sheridan_LEMA_5Mile_COMPLETE.dta", clear

        * Add in Water and Weather (Dataset 3)
        merge 1:m WR_ID PDIV_ID using "..\Water_Use_WEATHER_WR.dta", ///
        keep(match)

        *Already limited to D-I-D groups, but confirm below

        drop if LEMA == .
        drop if FIVE_MILE == .
        sort WUA_YEAR

        *Already limited to Irrigated Users, but confirm below

        keep if UMW_CODE == "IRR"


//Step 5: Create a pre/post LEMA Policy Variable

        gen postLEMA = 0
        replace postLEMA = 1 if WUA_YEAR >= 2013
        generate LEMA_EFFECT = postLEMA*LEMA

//Step 6: Create Crop and Irrigation Code Variables

*Create a variable that indicates the proportion of each observation planted to
*each crop and account for crop codes with multiple crops

        gen ALFALFA=0
        replace ALFALFA=. if CROP_CODE==.
        replace ALFALFA=1 if CROP_CODE==1
        replace ALFALFA=1/2 if CROP_CODE==18 | CROP_CODE==19 | CROP_CODE==20 | ///
        CROP_CODE==21 | CROP_CODE==22
        replace ALFALFA=1/3 if CROP_CODE==33 | CROP_CODE==34 | CROP_CODE==35 | ///
        CROP_CODE==36 | CROP_CODE==37 | CROP_CODE==38 | CROP_CODE==39 | ///
        CROP_CODE==40 | CROP_CODE==41 | CROP_CODE==42
        replace ALFALFA=1/4 if CROP_CODE==53 | CROP_CODE==54 | CROP_CODE==55 | ///
        CROP_CODE==56 | CROP_CODE==57 | CROP_CODE==58 | CROP_CODE==59 | ///
        CROP_CODE==60 | CROP_CODE==61 | CROP_CODE==62

        gen CORN=0
        replace CORN=. if CROP_CODE==.
        replace CORN=1 if CROP_CODE==2
        replace CORN=1/2 if CROP_CODE==18 | CROP_CODE==23 | CROP_CODE==24 | ///
        CROP_CODE==25 | CROP_CODE==26
        replace CORN=1/3 if CROP_CODE==33 | CROP_CODE==34 | CROP_CODE==35 | ///
        CROP_CODE==36 | CROP_CODE==43 | CROP_CODE==44 | CROP_CODE==45 | ///
        CROP_CODE==46 | CROP_CODE==47 | CROP_CODE==48
        replace CORN=1/4 if CROP_CODE==53 | CROP_CODE==54 | CROP_CODE==55 | ///
        CROP_CODE==56 | CROP_CODE==57 | CROP_CODE==58 | CROP_CODE==63 | ///
        CROP_CODE==64 | CROP_CODE==65 | CROP_CODE==66

        gen SORGHUM=0
        replace SORGHUM=. if CROP_CODE==.
        replace SORGHUM=1 if CROP_CODE==3
        replace SORGHUM=1/2 if CROP_CODE==19 | CROP_CODE==23 | CROP_CODE==27 | ///
        CROP_CODE==28 | CROP_CODE==29
        replace SORGHUM=1/3 if CROP_CODE==33 | CROP_CODE==37 | CROP_CODE==38 | ///
        CROP_CODE==39 | CROP_CODE==43 | CROP_CODE==44 | CROP_CODE==45 | ///
        CROP_CODE==49 | CROP_CODE==50 | CROP_CODE==51
        replace SORGHUM=1/4 if CROP_CODE==53 | CROP_CODE==54 | CROP_CODE==55 | ///
        CROP_CODE==59 | CROP_CODE==60 | CROP_CODE==61 | CROP_CODE==63 | ///
        CROP_CODE==64 | CROP_CODE==65 | CROP_CODE==67

        gen SOYBEAN=0
        replace SOYBEAN=. if CROP_CODE==.
        replace SOYBEAN=1 if CROP_CODE==4
        replace SOYBEAN=1/2 if CROP_CODE==20 | CROP_CODE==24 | CROP_CODE==27 | ///
        CROP_CODE==30 | CROP_CODE==31
```

```
        replace SOYBEAN=1/3 if CROP_CODE==34 | CROP_CODE==37 | CROP_CODE==40 | ///
        CROP_CODE==41 | CROP_CODE==43 | CROP_CODE==46 | CROP_CODE==47 | ///
        CROP_CODE==49 | CROP_CODE==50 | CROP_CODE==52
        replace SOYBEAN=1/4 if CROP_CODE==53 | CROP_CODE==56 | CROP_CODE==57 | ///
        CROP_CODE==59 | CROP_CODE==60 | CROP_CODE==62 | CROP_CODE==63 | ///
        CROP_CODE==64 | CROP_CODE==66 | CROP_CODE==67

        gen WHEAT=0
        replace WHEAT=. if CROP_CODE==.
        replace WHEAT=1 if CROP_CODE==5
        replace WHEAT=1/2 if CROP_CODE==21 | CROP_CODE==25 | CROP_CODE==28 | ///
        CROP_CODE==30 | CROP_CODE==32
        replace WHEAT=1/3 if CROP_CODE==35 | CROP_CODE==38 | CROP_CODE==40 | ///
        CROP_CODE==42 | CROP_CODE==44 | CROP_CODE==46 | CROP_CODE==48 | ///
        CROP_CODE==49 | CROP_CODE==51 | CROP_CODE==52
        replace WHEAT=1/4 if CROP_CODE==54 | CROP_CODE==56 | CROP_CODE==58 | ///
        CROP_CODE==59 | CROP_CODE==61 | CROP_CODE==62 | CROP_CODE==63 | ///
        CROP_CODE==65 | CROP_CODE==66 | CROP_CODE==67

        gen MULTIPLE_UNKNOWN=0
        replace MULTIPLE_UNKNOWN=. if CROP_CODE==.
        replace MULTIPLE_UNKNOWN=1 if CROP_CODE==16 | CROP_CODE==17

        gen OTHER_CROP=0
        replace OTHER_CROP=. if CROP_CODE==.
        replace OTHER_CROP=1 if CROP_CODE==6 | CROP_CODE==7 | CROP_CODE==8 | ///
        CROP_CODE==9 | CROP_CODE==10 | CROP_CODE==11 | CROP_CODE==12 | ///
        CROP_CODE==13 | CROP_CODE==14 | CROP_CODE==15 | CROP_CODE==68 | ///
        CROP_CODE==69 | CROP_CODE==70 | CROP_CODE==71 | CROP_CODE==72 | ///
        CROP_CODE==73 | CROP_CODE==74 | CROP_CODE==75 | CROP_CODE==76 | ///
        CROP_CODE==77 | CROP_CODE==78

*Create dummy variables for each irrigation system

        generate IRR_FLOOD = 0
        replace IRR_FLOOD = . if TYPE_SYSTEM == .
        replace IRR_FLOOD = 1 if TYPE_SYSTEM == 1

        generate IRR_DRIP = 0
        replace IRR_DRIP = . if TYPE_SYSTEM == .
        replace IRR_DRIP = 1 if TYPE_SYSTEM == 2

        generate IRR_PIVOT = 0
        replace IRR_PIVOT = . if TYPE_SYSTEM == .
        replace IRR_PIVOT = 1 if TYPE_SYSTEM == 3

        generate IRR_PIVOTDROP = 0
        replace IRR_PIVOTDROP = . if TYPE_SYSTEM == .
        replace IRR_PIVOTDROP = 1 if TYPE_SYSTEM == 4

        generate IRR_SPRINKLER = 0
        replace IRR_SPRINKLER = . if TYPE_SYSTEM == .
        replace IRR_SPRINKLER = 1 if TYPE_SYSTEM == 5

        generate IRR_PIVOTFLOOD = 0
        replace IRR_PIVOTFLOOD = . if TYPE_SYSTEM == .
        replace IRR_PIVOTFLOOD = 1 if TYPE_SYSTEM == 6

        generate IRR_DRIPOTHER = 0
        replace IRR_DRIPOTHER = . if TYPE_SYSTEM == .
        replace IRR_DRIPOTHER = 1 if TYPE_SYSTEM == 7

        generate IRR_OTHER = 0
        replace IRR_OTHER = . if TYPE_SYSTEM == .
        replace IRR_OTHER = 1 if TYPE_SYSTEM == 8

//Step 7: Estimate the means of each ACRES IRR, ACRE FEET USED, WEATHER,
//CROP TYPE and SYSTEM variable using a weighted mean using acres irrigated as the
//weight. (This creates the proportion of acres of a water right planted to a
//particular crop)
```

```
        collapse (rawsum) AF_USED ACRES_IRR (mean) ppt ET0 ALFALFA CORN
        SORGHUM SOYBEAN WHEAT MULTIPLE_UNKNOWN OTHER_CROP IRR_FLOOD IRR_DRIP ///
        IRR_PIVOT IRR_PIVOTDROP IRR_SPRINKLER IRR_PIVOTFLOOD IRR_DRIPOTHER ///
        IRR_OTHER LEMA FIVE_MILE postLEMA LEMA_EFFECT [aweight=ACRES_IRR], ///
                by(WUA_YEAR WR_ID WUAPERS_ID TACRES_IRR NACRES_IRR)
        sort WR_ID WUA_YEAR
        duplicates report WR_ID WUA_YEAR
        sum

        *Create Intensive marginal variables

        gen APPLIED_INCH = (AF_USED*12)
        gen INTENSITY = (APPLIED_INCH/ACRES_IRR)

        *Final Water Policy D-I-D data with WR_ID and PDIV_ID (Dataset 4)

        ********************************************
        save "..\DID_LEMA_Dataset_WEATHER_WR.dta", replace
        clear
        ********************************************

clear
set more off


*******************************************************************************
                                //ANALYSIS//
*******************************************************************************

//Step 1: Set up the Model and generate log-form dependent variables
//Following the methodology in Hendricks and Peterson (2012) to calculate
//Marginal Effects but using the log form to obtain straghtforward
//interpretations of the coefficients as elasticities

        use "..\DID_LEMA_Dataset_WEATHER_WR.dta"
        xtset WR_ID WUA_YEAR, yearly
        keep if WUA_YEAR>=2009
        xtdescribe

        gen lnAPPLIED_INCH=ln(APPLIED_INCH)
        gen lnACRES_IRR=ln(ACRES_IRR)
        gen lnINTENSITY=ln(INTENSITY)

*Table 1: Summary Statistics of D-I-D Groups Comparison of Means Pre-Policy

*Following Villa (2014) balancing t-test of the difference in the means of the
*covariates between the control and treated groups in period == 0 based on the
*kernel weight.

        diff lnAPPLIED_INCH lnACRES_IRR lnINTENSITY, t(LEMA) p(postLEMA) kernel ///
        cov(IRR_FLOOD IRR_DRIP IRR_PIVOT IRR_PIVOTDROP IRR_SPRINKLER ///
        IRR_PIVOTFLOOD IRR_DRIPOTHER IRR_OTHER ALFALFA CORN SORGHUM ///
        SOYBEAN WHEAT MULTIPLE_UNKNOWN OTHER_CROP ppt ET0 ) id(WR_ID) ///
        robust cluster(WR_ID) test

        diff lnACRES_IRR lnACRES_IRR lnINTENSITY, t(LEMA) p(postLEMA) kernel ///
        cov(IRR_FLOOD IRR_DRIP IRR_PIVOT IRR_PIVOTDROP IRR_SPRINKLER ///
        IRR_PIVOTFLOOD IRR_DRIPOTHER IRR_OTHER ALFALFA CORN SORGHUM ///
        SOYBEAN WHEAT MULTIPLE_UNKNOWN OTHER_CROP ppt ET0 ) id(WR_ID) ///
        robust cluster(WR_ID) test

        diff lnINTENSITY lnACRES_IRR lnINTENSITY, t(LEMA) p(postLEMA) kernel ///
        cov(IRR_FLOOD IRR_DRIP IRR_PIVOT IRR_PIVOTDROP IRR_SPRINKLER ///
        IRR_PIVOTFLOOD IRR_DRIPOTHER IRR_OTHER ALFALFA CORN SORGHUM ///
        SOYBEAN WHEAT MULTIPLE_UNKNOWN OTHER_CROP ppt ET0 ) id(WR_ID) ///
        robust cluster(WR_ID) test

        summ IRR_FLOOD IRR_DRIP IRR_PIVOT IRR_PIVOTDROP IRR_SPRINKLER ///
        IRR_PIVOTFLOOD IRR_DRIPOTHER IRR_OTHER ALFALFA CORN SORGHUM ///
        SOYBEAN WHEAT MULTIPLE_UNKNOWN OTHER_CROP ppt ET0
```

```
*Average Treatment Effect on the Treated
        summ LEMA LEMA_EFFECT postLEMA if LEMA==1

//Step 2: Visual Analysis (D-I-D)

        *Figure 6: Total Extensive and Intensive Marginal Effects
        egen A_PRE_ALL = mean(ACRES_IRR)     if WUA_YEAR <= 2012 and LEMA == 1
        egen A_POST_ALL = mean(ACRES_IRR)     if WUA_YEAR >  2012 and LEMA == 1
        egen A_FIVEPRE_ALL = mean(ACRES_IRR)  if WUA_YEAR <= 2012 and LEMA == 0
        egen A_FIVEPOST_ALL = mean(ACRES_IRR) if WUA_YEAR >  2012 and LEMA == 0

        egen I_PRE_ALL = mean(INTENSITY)     if WUA_YEAR <= 2012 and LEMA == 1
        egen I_POST_ALL = mean(INTENSITY)     if WUA_YEAR >  2012 and LEMA == 1
        egen I_FIVEPRE_ALL = mean(INTENSITY)  if WUA_YEAR <= 2012 and LEMA == 0
        egen I_FIVEPOST_ALL = mean(INTENSITY) if WUA_YEAR >  2012 and LEMA == 0

        *Figure 7: Crop Specific Extensive Marginal Effects
        egen A_PRE_ALF = mean(ACRES_IRR*ALFALFA) if WUA_YEAR <= 2012 and LEMA ==
        1 egen A_PRE_CRN = mean(ACRES_IRR*CORN) if WUA_YEAR <= 2012 and LEMA == 1
        egen A_PRE_SOR = mean(ACRES_IRR*SORGHUM) if WUA_YEAR <= 2012 and LEMA ==
        1 egen A_PRE_SOY = mean(ACRES_IRR*SOYBEAN) if WUA_YEAR <= 2012 and LEMA
        == 1 egen A_PRE_WHT = mean(ACRES_IRR*WHEAT)   if WUA_YEAR <= 2012 and LEMA
        == 1
        egen A_PRE_MLT = mean(ACRES_IRR*MULTIPLE_UNKNOWN)  ///
        if WUA_YEAR <= 2012 and LEMA == 1

        egen A_POST_ALF = mean(ACRES_IRR*ALFALFA) if WUA_YEAR > 2012 and LEMA ==
        1 egen A_POST_CRN = mean(ACRES_IRR*CORN) if WUA_YEAR > 2012 and LEMA == 1
        egen A_POST_SOR = mean(ACRES_IRR*SORGHUM) if WUA_YEAR > 2012 and LEMA ==
        1 egen A_POST_SOY = mean(ACRES_IRR*SOYBEAN) if WUA_YEAR > 2012 and LEMA
        == 1 egen A_POST_WHT = mean(ACRES_IRR*WHEAT) if WUA_YEAR > 2012 and LEMA
        == 1
        egen A_POST_MLT = mean(ACRES_IRR*MULTIPLE_UNKNOWN) ///
        if WUA_YEAR > 2012 and LEMA == 1

        egen A_FIVEPRE_ALF = mean(ACRES_IRR*ALFALFA) if WUA_YEAR <= 2012 and LEMA ==
        0 egen A_FIVEPRE_CRN = mean(ACRES_IRR*CORN) if WUA_YEAR <= 2012 and LEMA == 0
        egen A_FIVEPRE_SOR = mean(ACRES_IRR*SORGHUM) if WUA_YEAR <= 2012 and LEMA ==
        0 egen A_FIVEPRE_SOY = mean(ACRES_IRR*SOYBEAN) if WUA_YEAR <= 2012 and LEMA ==
        0 egen A_FIVEPRE_WHT = mean(ACRES_IRR*WHEAT)   if WUA_YEAR <= 2012 and LEMA
        == 0
        egen A_FIVEPRE_MLT = mean(ACRES_IRR*MULTIPLE_UNKNOWN)   ///
        if WUA_YEAR <= 2012 and LEMA == 0

        egen A_FIVEPOST_ALF = mean(ACRES_IRR*ALFALFA) if WUA_YEAR > 2012 and LEMA ==
        0 egen A_FIVEPOST_CRN = mean(ACRES_IRR*CORN) if WUA_YEAR > 2012 and LEMA == 0
        egen A_FIVEPOST_SOR = mean(ACRES_IRR*SORGHUM) if WUA_YEAR > 2012 and LEMA ==
        0 egen A_FIVEPOST_SOY = mean(ACRES_IRR*SOYBEAN) if WUA_YEAR > 2012 and LEMA ==
        0 egen A_FIVEPOST_WHT = mean(ACRES_IRR*WHEAT) if WUA_YEAR > 2012 and LEMA ==
        0 egen A_FIVEPOST_MLT = mean(ACRES_IRR*MULTIPLE_UNKNOWN)  ///
        if WUA_YEAR > 2012 and LEMA == 0


        *Table of summary statistics
        summ
        *Additional analysis done in excel to generate "counterfactual" and graphs

        * Crop Specific Intensive Marginal Effects
        mean INTENSITY if WUA_YEAR <= 2012 and LEMA == 1 and
        ALFALFA==1 mean INTENSITY if WUA_YEAR > 2012 and LEMA == 1
        and ALFALFA==1 mean INTENSITY if WUA_YEAR <= 2012 and LEMA
        == 0 and ALFALFA==1 mean INTENSITY if WUA_YEAR > 2012 and
        LEMA == 0 and ALFALFA==1

        mean INTENSITY if WUA_YEAR <= 2012 and LEMA == 1 and
        CORN==1 mean INTENSITY if WUA_YEAR > 2012 and LEMA == 1
        and CORN==1 mean INTENSITY if WUA_YEAR <= 2012 and LEMA
        == 0 and CORN==1 mean INTENSITY if WUA_YEAR > 2012 and
        LEMA == 0 and CORN==1
```

```
        capture mean INTENSITY if WUA_YEAR <= 2012 and LEMA == 1 and
        SORGHUM==1 mean INTENSITY if WUA_YEAR > 2012 and LEMA == 1 and
        SORGHUM==1
        mean INTENSITY if WUA_YEAR <= 2012 and LEMA == 0 and
        SORGHUM==1 mean INTENSITY if WUA_YEAR > 2012 and LEMA == 0 and
        SORGHUM==1

        mean INTENSITY if WUA_YEAR <= 2012 and LEMA == 1 and
        SOYBEAN==1 mean INTENSITY if WUA_YEAR > 2012 and LEMA == 1
        and SOYBEAN==1 mean INTENSITY if WUA_YEAR <= 2012 and LEMA
        == 0 and SOYBEAN==1 mean INTENSITY if WUA_YEAR > 2012 and
        LEMA == 0 and SOYBEAN==1

        mean INTENSITY if WUA_YEAR <= 2012 and LEMA == 1 and
        WHEAT==1 mean INTENSITY if WUA_YEAR > 2012 and LEMA == 1
        and WHEAT==1 mean INTENSITY if WUA_YEAR <= 2012 and LEMA ==
        0 and WHEAT==1 mean INTENSITY if WUA_YEAR > 2012 and LEMA
        == 0 and WHEAT==1

        mean INTENSITY if WUA_YEAR <= 2012 and LEMA == 1 and
        MULTIPLE_UNKNOWN==1 mean INTENSITY if WUA_YEAR > 2012 and LEMA == 1
        and MULTIPLE_UNKNOWN==1 mean INTENSITY if WUA_YEAR <= 2012 and LEMA
        == 0 and MULTIPLE_UNKNOWN==1 mean INTENSITY if WUA_YEAR > 2012 and
        LEMA == 0 and MULTIPLE_UNKNOWN==1

        mean ppt if WUA_YEAR <= 2012 and LEMA == 1
        mean ppt if WUA_YEAR > 2012 and LEMA == 1
        mean ppt if WUA_YEAR <= 2012 and LEMA == 0
        mean ppt if WUA_YEAR > 2012 and LEMA == 0

        * IRR_FLOOD IRR_DRIP IRR_PIVOT IRR_PIVOTDROP IRR_SPRINKLER
        gen flood_acres= ACRES_IRR*IRR_FLOOD
        gen pivotdrop_acres=ACRES_IRR*IRR_PIVOTDROP
        gen pivot_acres=ACRES_IRR*IRR_PIVOT

        mean flood_acres if WUA_YEAR <= 2012 and LEMA == 1
        mean flood_acres if WUA_YEAR > 2012 and LEMA == 1
        mean flood_acres if WUA_YEAR <= 2012 and LEMA == 0
        mean flood_acres if WUA_YEAR > 2012 and LEMA == 0

        mean pivotdrop_acres if WUA_YEAR <= 2012 and LEMA ==
        1 mean pivotdrop_acres if WUA_YEAR > 2012 and LEMA ==
        1 mean pivotdrop_acres if WUA_YEAR <= 2012 and LEMA
        == 0 mean pivotdrop_acres if WUA_YEAR > 2012 and LEMA
        == 0

        mean pivot_acres if WUA_YEAR <= 2012 and LEMA == 1
        mean pivot_acres if WUA_YEAR > 2012 and LEMA == 1
        mean pivot_acres if WUA_YEAR <= 2012 and LEMA == 0
        mean pivot_acres if WUA_YEAR > 2012 and LEMA == 0

//Step 3: Marginal Estimates

*Table 2: Preferred Model Fixed Effects regression estimates

        *Generate Farmer-Time Specific Variables

        egen f = group(WUAPERS_ID)
        egen FARMER = group(WUAPERS_ID WUA_YEAR)
        sort f
        set matsize 1500
        set emptycells drop

        * Total Extensive Margin

        xtreg lnACRES_IRR LEMA_EFFECT ppt ET0 i.FARMER i.WUA_YEAR, ///
        fe vce(cluster WR_ID)

        *Apply Log-Linear Correction
        nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
        estimates store EXTENSIVE
```

```
        * Total Intensive Margin

        xtreg lnINTENSITY LEMA_EFFECT ppt ET0 i.FARMER i.WUA_YEAR, ///
        fe vce(cluster WR_ID)

        *Apply Log-Linear Correction
        nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
        estimates store INTENSIVE

        * Direct Intensive Margin (Crop Controls)

        xtreg lnINTENSITY LEMA_EFFECT ALFALFA CORN SORGHUM SOYBEAN WHEAT ppt ET0 ///
        i.FARMER i.WUA_YEAR, fe vce(cluster WR_ID)

        *Apply Log-Linear Correction
        nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
        estimates store INTENSIVE_DIRECT_1

        estimates table EXTENSIVE INTENSIVE INTENSIVE_DIRECT_1 ///
        ,star stats(N r2 r2_a)

*Table 3: Preferred Model Fixed Effects regression estimates

        *Indirect Intensive Margin

        //(You can get the effect due to changes in cropping patterns by
        //taking the Total Intensive - Direct Intensive)

        *Total Marginal Effect

        xtreg lnAPPLIED_INCH LEMA_EFFECT i.FARMER i.WUA_YEAR ppt ET0, ///
        fe vce(cluster WR_ID)

        *Apply Log-Linear Correction
        nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
        estimates store TOTAL

//Step 4: Modification to consider disporportionate water use
        clear
        set more off
        use "..\DID_LEMA_Dataset_WR_PDIV.dta"
        keep if WUA_YEAR>=2009
        keep if LEMA ==1

        *Generate Farmer-Time Specific Variables

        egen f = group(WUAPERS_ID)
        egen FARMER = group(WUAPERS_ID WUA_YEAR)
        sort f
        set matsize 1500
        set emptycells drop

        *Count PDIV by Year and Irrigator ID (# of wells)
        gen A=PDIV_ID

        collapse (count)A, ///
                by(WUA_YEAR WUAPERS_ID)
                sort WUAPERS_ID WUA_YEAR

        merge 1:m WUA_YEAR WUAPERS_ID using "..\DID_LEMA_Dataset_WEATHER_WR.dta",///
        keep(match using)
        drop _merge

        *Generate Large Well Dummy Variable
        gen LARGE= 0
        replace LARGE =1 if A>=2 and LEMA==1
        summ LARGE
        gen LEMA_LARGE = (LEMA_EFFECT*LARGE)
```

```
        xtset WR_ID WUA_YEAR
        xtdescribe

*Table 4: Disproportionate Fixed Effects

        *Generate Farmer-Time Specific Variables

        egen f = group(WUAPERS_ID)
        egen FARMER = group(WUAPERS_ID WUA_YEAR)
        sort f
        set matsize 1500
        set emptycells drop

        gen lnAPPLIED_INCH=ln(APPLIED_INCH)
        gen lnACRES_IRR=ln(ACRES_IRR)
        gen lnINTENSITY=ln(INTENSITY)

        xtreg lnAPPLIED_INCH LEMA_EFFECT LEMA_LARGE i.FARMER i.WUA_YEAR ppt ET0, ///
        fe vce(cluster WR_ID)
        *Apply Log-Linear Correction
        nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
        nlcom ((exp(_b[LEMA_LARGE]))-1)*100
        estimates store L_TOTAL

        xtreg lnINTENSITY LEMA_EFFECT LEMA_LARGE i.FARMER i.WUA_YEAR ppt ET0, ///
        fe vce(cluster WR_ID)
        *Apply Log-Linear Correction
        nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
        nlcom ((exp(_b[LEMA_LARGE]))-1)*100
        estimates store L_INTENSITY

        xtreg lnACRES_IRR LEMA_EFFECT LEMA_LARGE i.FARMER i.WUA_YEAR ppt ET0, ///
        fe vce(cluster WR_ID)
        *Apply Log-Linear Correction

        nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
        nlcom ((exp(_b[LEMA_LARGE]))-1)*100
        estimates store L_ACRES_IRR

        estimates table L_TOTAL L_INTENSITY L_ACRES_IRR ,star stats(N r2 r2_a)



//Step 5: Water Policy Event Study

        set more off
        clear
        use "..\DID_LEMA_Dataset_WEATHER_WR.dta"
        xtset WR_ID WUA_YEAR, yearly
        keep if WUA_YEAR>=2009

        *Generate Farmer-Time Specific Variables

        egen f = group(WUAPERS_ID)
        egen FARMER = group(WUAPERS_ID WUA_YEAR)
        sort f
        set matsize 1500
        set emptycells drop
        sort WR_ID WUA_YEAR

        gen lnAPPLIED_INCH=ln(APPLIED_INCH)
        gen lnACRES_IRR=ln(ACRES_IRR)
        gen lnINTENSITY=ln(INTENSITY)
        gen Policy_Event=0

        replace Policy_Event=1 if d.LEMA_EFFECT==1
        gen _2014=0
        replace _2014=1 if L1.Policy_Event==1
        gen _2012=0
        replace _2012=1 if F1.Policy_Event==1
        gen _2011=0
```

```
        replace _2011=1 if F2.Policy_Event==1
        gen _2010=0
        replace _2010=1 if F3.Policy_Event==1
        gen _2009=0
        replace _2009=1 if F4.Policy_Event==1

        label var _2010 "2010"

*Figure 9: Total Extensive and Total Intensive

        * Total Effect
        set scheme s2mono
        xtreg lnAPPLIED_INCH _2010 _2011 _2012 Policy_Event _2014 i.FARMER ///
        i.WUA_YEAR ppt ET0, fe vce(cluster WR_ID)
        margins, dydx (_2010 _2011 _2012 Policy_Event _2014)
        marginsplot, yline(0)   plotopts(connect(i)) ///
        xlabel(1 "2010" 2 "2011" 3 "2012" 4 "Policy Event" 5 "2014") ///
        xtitle("") ytitle("Relative Change in Water Use") title("Total Response")///
        graphregion(color(white)) scale(1.25) ylabel(,nogrid)
        graph export "..\..\Dissertation\Dissertation\EventStudy\Total_1.pdf",
        replace

        * Total Extensive Margin

        xtreg lnACRES_IRR _2010 _2011 _2012 Policy_Event _2014 i.FARMER ///
        i.WUA_YEAR ppt ET0, fe vce(cluster WR_ID)
        margins, dydx ( _2010 _2011 _2012 Policy_Event _2014)
        marginsplot, yline(0)   plotopts(connect(i)) ///
        xlabel(1 "2010" 2 "2011" 3 "2012" 4 "Policy Event" 5 "2014") ///
        xtitle("") ytitle("Relative Change in Water Use") title
        ("Extensive Margin Response") ///
        graphregion(color(white)) scale(1.25) ylabel(,nogrid)
        graph export "..\..\Dissertation\Dissertation\EventStudy\Extensive_1.pdf",
        replace

        * Total Intensive Margin

        xtreg lnINTENSITY _2010 _2011 _2012 Policy_Event _2014 i.FARMER ///
        i.WUA_YEAR ppt ET0, fe vce(cluster WR_ID)
        margins, dydx (_2010 _2011 _2012 Policy_Event _2014)
        marginsplot, yline(0)   plotopts(connect(i))
        xlabel(1 "2010" 2 "2011" 3 "2012" 4 "Policy Event" 5 "2014") ///
        xtitle("") ytitle("Relative Change in Water Use")
        title("Total Intensive Margin Response") ///
        graphregion(color(white)) scale(1.25) ylabel(,nogrid)
        graph export "..\..\Dissertation\Dissertation\EventStudy\Intensive_1.pdf",
        replace

        * Direct Intensive Margin

        xtreg lnINTENSITY _2010 _2011 _2012 Policy_Event _2014 ALFALFA CORN ///
        SORGHUM SOYBEAN WHEAT i.FARMER i.WUA_YEAR ppt ET0, fe vce(cluster WR_ID)
        margins, dydx (_2010 _2011 _2012 Policy_Event _2014)
        marginsplot, yline(0)   plotopts(connect(i))
        xlabel(1 "2010" 2 "2011" 3 "2012" 4 "Policy Event" 5 "2014") ///
        xtitle("") ytitle("Relative Change in Water Use")
        title("Direct Intensive Margin Response") ///
        graphregion(color(white)) scale(1.25) ylabel(,nogrid)
        replace
        graph export "..\..\Dissertation\Dissertation\EventStudy\
        Intensive_Direct.pdf", replace

//Step 6: Compare Estimates with alternative specifications

*Table 4:Log (Total Effect) Applied Inches

        *The Standard D-I-D specification with no controls
        xtreg lnAPPLIED_INCH LEMA_EFFECT i.WUA_YEAR , fe vce(cluster WR_ID)
        *Apply Log-Linear Correction
        nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
        estimates store DID
```

```
        *Fixed Effects Model Without Farmer-Time Specific Controls
        xtreg lnAPPLIED_INCH LEMA_EFFECT ppt ET0 i.WUA_YEAR , fe vce(cluster WR_ID)
        *Apply Log-Linear Correction
        nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
        estimates store FARMER

        *Fixed Effects Model Without Weather Controls
        xtreg lnAPPLIED_INCH LEMA_EFFECT i.FARMER i.WUA_YEAR, fe vce(cluster WR_ID)
        *Apply Log-Linear Correction
        nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
        estimates store WEATHER

        *Fixed Effects Model As Specified
        xtreg lnAPPLIED_INCH LEMA_EFFECT ppt ET0 i.FARMER i.WUA_YEAR, ///
        fe vce(cluster WR_ID)

        *Apply Log-Linear Correction
        nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
        estimates store NO_CORRECT

        estimates table DID FARMER WEATHER NO_CORRECT,star stats(N r2 r2_a)

//Step 7: Falsification Tests

*Table 9: Comparison of 5 Mile and 10 Mile (identical steps as LEMA and 5 Mile)
        ********************************(Still need to modify Weather merge)******
        *Create 10 mile and 5 Mile Dataset
        clear
        set more off
        import delimited "..\dataAnalysis\Model and Output files\5 Mile PDIV\
        Sheridan_LEMA_5Mile_Export_Output.csv"
        duplicates drop fpdiv_key, force
        generate FIVE_MILE = 1
        generate TEN_MILE = 0
        drop fid wrf_active right_type vcnty_code wr_num wr_qual wrf_status ///
        source s_umw priority fpv_active twp_dir rng_dir dwr_id feet_north ///
        feet_west qual_four qual_three qual_two qual_one fo_num basin_num ///
        basin_name gwmd_num cnty_abrev sua_code stream_num num_wells lot_number ///
        lot_qual1 lot_qual2 fpdiv_comm fpdiv_key wrf_key longitude latitude ///
        quant_id quant_unit qstor_ind rate_id rate_unit rstor_ind last_name ///
        first_name wris_date file_id auth_quant add_quant auth_rate add_rate ///
        sect rng twp grp_wr_cnt grp_pd_cnt
        generate WR_ID = wr_id
        drop wr_id
        generate PDIV_ID = pdiv_id
        drop pdiv_id
        generate UMW_CODE = umw_code
        drop umw_code
        keep if UMW_CODE=="IRR"
        egen unique = concat (WR_ID PDIV_ID)
        duplicates report unique
        save "..\dataAnalysis\Model and Output files\5 Mile PDIV\
        Cleaned_10_Mile_5Mile_Export_Output.dta", replace
        clear
        import delimited "..\dataRaw\PDIV_10Mile.csv",
        duplicates drop fpdiv_key, force
        generate TEN_MILE = 1
        generate FIVE_MILE = 0
        drop fid wrf_active right_type vcnty_code wr_num wr_qual wrf_status ///
        source s_umw priority fpv_active twp_dir rng_dir dwr_id feet_north ///
        feet_west qual_four qual_three qual_two qual_one fo_num basin_num ///
        basin_name gwmd_num cnty_abrev sua_code stream_num num_wells lot_number ///
        lot_qual1 lot_qual2 fpdiv_comm fpdiv_key wrf_key longitude latitude ///
        quant_id quant_unit qstor_ind rate_id rate_unit rstor_ind last_name ///
        first_name wris_date file_id auth_quant add_quant auth_rate add_rate ///
        sect rng twp grp_wr_cnt grp_pd_cnt
        destring wr_id, generate(WR_ID) ignore(",") float
        drop wr_id
        destring pdiv_id, generate(PDIV_ID) ignore(",") float
        drop pdiv_id
```

```
destring wr_group, generate(WR_GROUP) ignore(",") float
drop wr_group
generate UMW_CODE = umw_code
drop umw_code
keep if UMW_CODE=="IRR"
egen unique = concat (WR_ID PDIV_ID)
duplicates report unique
save "..\dataAnalysis\Model and Output files\5 Mile PDIV\
Cleaned_10_MILE_Export_Output.dta", replace
append using "..\dataAnalysis\Model and Output files\
5 Mile PDIV\Cleaned_10_Mile_5Mile_Export_Output.dta", force
duplicates report unique
generate TACRES_IRR = tacres_irr

drop tacres_irr
generate NACRES_IRR = nacres_irr
drop nacres_irr
duplicates report WR_ID PDIV_ID
duplicates tag WR_ID PDIV_ID, gen(dup)
list if dup==1
drop if dup==1 and FIVE_MILE==1
duplicates report WR_ID PDIV_ID
drop dup
save "..\dataAnalysis\Model and Output files\5 Mile PDIV\
Cleaned_10_Mile_5Mile_COMPLETE.dta", replace
clear
use "..\dataRaw\Cleaned_Water_Use_1991_2014_Export_Output.dta", clear
keep if CNTY_ABREV=="TH" | CNTY_ABREV=="SH"
keep if UMW_CODE == "IRR"
duplicates report unique WUA_YEAR
duplicates drop
merge m:1 WR_ID PDIV_ID UMW_CODE using "..\dataAnalysis\
Model and Output files\5 Mile PDIV\Cleaned_10_Mile_5Mile_COMPLETE.dta",
keep(match) force
save "..\dataRaw\Cleaned_Water_Use_1991_2014_With10Mileand5Mile.dta",
replace  drop if TEN_MILE == .
drop if FIVE_MILE == .
sort WUA_YEAR
gen postLEMA = 0
replace postLEMA = 1 if WUA_YEAR >= 2013
generate LEMA_EFFECT = postLEMA*FIVE_MILE
sort WR_ID WUA_YEAR
gen ALFALFA=0
replace ALFALFA=. if CROP_CODE==.
replace ALFALFA=1 if CROP_CODE==1
replace ALFALFA=1/2 if CROP_CODE==18 | CROP_CODE==19 | CROP_CODE==20 | ///
CROP_CODE==21 | CROP_CODE==22
replace ALFALFA=1/3 if CROP_CODE==33 | CROP_CODE==34 | CROP_CODE==35 | ///
CROP_CODE==36 | CROP_CODE==37 | CROP_CODE==38 | CROP_CODE==39 | ///
CROP_CODE==40 | CROP_CODE==41 | CROP_CODE==42
replace ALFALFA=1/4 if CROP_CODE==53 | CROP_CODE==54 | CROP_CODE==55 | ///
CROP_CODE==56 | CROP_CODE==57 | CROP_CODE==58 | CROP_CODE==59 | ///
CROP_CODE==60 | CROP_CODE==61 | CROP_CODE==62
gen CORN=0
replace CORN=. if CROP_CODE==.
replace CORN=1 if CROP_CODE==2
replace CORN=1/2 if CROP_CODE==18 | CROP_CODE==23 | CROP_CODE==24 | ///
CROP_CODE==25 | CROP_CODE==26
replace CORN=1/3 if CROP_CODE==33 | CROP_CODE==34 | CROP_CODE==35 | ///
CROP_CODE==36 | CROP_CODE==43 | CROP_CODE==44 | CROP_CODE==45 | ///
CROP_CODE==46 | CROP_CODE==47 | CROP_CODE==48
replace CORN=1/4 if CROP_CODE==53 | CROP_CODE==54 | CROP_CODE==55 | ///
CROP_CODE==56 | CROP_CODE==57 | CROP_CODE==58 | CROP_CODE==63 | ///
CROP_CODE==64 | CROP_CODE==65 | CROP_CODE==66
gen SORGHUM=0
replace SORGHUM=. if CROP_CODE==.
replace SORGHUM=1 if CROP_CODE==3
replace SORGHUM=1/2 if CROP_CODE==19 | CROP_CODE==23 | CROP_CODE==27 | ///
CROP_CODE==28 | CROP_CODE==29
```

```
replace SORGHUM=1/3 if CROP_CODE==33 | CROP_CODE==37 | CROP_CODE==38 | ///
CROP_CODE==39 | CROP_CODE==43 | CROP_CODE==44 | CROP_CODE==45 | ///
CROP_CODE==49 | CROP_CODE==50 | CROP_CODE==51
replace SORGHUM=1/4 if CROP_CODE==53 | CROP_CODE==54 | CROP_CODE==55 | ///
CROP_CODE==59 | CROP_CODE==60 | CROP_CODE==61 | CROP_CODE==63 | ///
CROP_CODE==64 | CROP_CODE==65 | CROP_CODE==67
gen SOYBEAN=0
replace SOYBEAN=. if CROP_CODE==.
replace SOYBEAN=1 if CROP_CODE==4
replace SOYBEAN=1/2 if CROP_CODE==20 | CROP_CODE==24 | CROP_CODE==27 | ///
CROP_CODE==30 | CROP_CODE==31
replace SOYBEAN=1/3 if CROP_CODE==34 | CROP_CODE==37 | CROP_CODE==40 | ///
CROP_CODE==41 | CROP_CODE==43 | CROP_CODE==46 | CROP_CODE==47 | ///
CROP_CODE==49 | CROP_CODE==50 | CROP_CODE==52
replace SOYBEAN=1/4 if CROP_CODE==53 | CROP_CODE==56 | CROP_CODE==57 | ///
CROP_CODE==59 | CROP_CODE==60 | CROP_CODE==62 | CROP_CODE==63 | ///
CROP_CODE==64 | CROP_CODE==66 | CROP_CODE==67
gen WHEAT=0
replace WHEAT=. if CROP_CODE==.
replace WHEAT=1 if CROP_CODE==5
replace WHEAT=1/2 if CROP_CODE==21 | CROP_CODE==25 | CROP_CODE==28 | ///
CROP_CODE==30 | CROP_CODE==32
replace WHEAT=1/3 if CROP_CODE==35 | CROP_CODE==38 | CROP_CODE==40 | ///
CROP_CODE==42 | CROP_CODE==44 | CROP_CODE==46 | CROP_CODE==48 | ///
CROP_CODE==49 | CROP_CODE==51 | CROP_CODE==52
replace WHEAT=1/4 if CROP_CODE==54 | CROP_CODE==56 | CROP_CODE==58 | ///
CROP_CODE==59 | CROP_CODE==61 | CROP_CODE==62 | CROP_CODE==63 | ///
CROP_CODE==65 | CROP_CODE==66 | CROP_CODE==67
gen MULTIPLE_UNKNOWN=0
replace MULTIPLE_UNKNOWN=. if CROP_CODE==.
replace MULTIPLE_UNKNOWN=1 if CROP_CODE==16 | CROP_CODE==17
gen OTHER_CROP=0
replace OTHER_CROP=. if CROP_CODE==.
replace OTHER_CROP=1 if CROP_CODE==6 | CROP_CODE==7 | CROP_CODE==8 | ///
CROP_CODE==9 | CROP_CODE==10 | CROP_CODE==11 | CROP_CODE==12 | ///
CROP_CODE==13 | CROP_CODE==14 | CROP_CODE==15 | CROP_CODE==68 | ///
CROP_CODE==69 | CROP_CODE==70 | CROP_CODE==71 | CROP_CODE==72 | ///
CROP_CODE==73 | CROP_CODE==74 | CROP_CODE==75 | CROP_CODE==76 | ///
CROP_CODE==77 | CROP_CODE==78


generate IRR_FLOOD = 0
replace IRR_FLOOD = . if TYPE_SYSTEM == .
replace IRR_FLOOD = 1 if TYPE_SYSTEM == 1
generate IRR_DRIP = 0
replace IRR_DRIP = . if TYPE_SYSTEM == .
replace IRR_DRIP = 1 if TYPE_SYSTEM == 2
generate IRR_PIVOT = 0
replace IRR_PIVOT = . if TYPE_SYSTEM == .
replace IRR_PIVOT = 1 if TYPE_SYSTEM == 3
generate IRR_PIVOTDROP = 0
replace IRR_PIVOTDROP = . if TYPE_SYSTEM == .
replace IRR_PIVOTDROP = 1 if TYPE_SYSTEM == 4
generate IRR_SPRINKLER = 0
replace IRR_SPRINKLER = . if TYPE_SYSTEM == .
replace IRR_SPRINKLER = 1 if TYPE_SYSTEM == 5
generate IRR_PIVOTFLOOD = 0
replace IRR_PIVOTFLOOD = . if TYPE_SYSTEM == .
replace IRR_PIVOTFLOOD = 1 if TYPE_SYSTEM == 6
generate IRR_DRIPOTHER = 0
replace IRR_DRIPOTHER = . if TYPE_SYSTEM == .
replace IRR_DRIPOTHER = 1 if TYPE_SYSTEM == 7
generate IRR_OTHER = 0
replace IRR_OTHER = . if TYPE_SYSTEM == .
replace IRR_OTHER = 1 if TYPE_SYSTEM == 8

collapse (rawsum) AF_USED ACRES_IRR (mean) ALFALFA CORN SORGHUM SOYBEAN ///
WHEAT MULTIPLE_UNKNOWN OTHER_CROP IRR_FLOOD IRR_DRIP IRR_PIVOT ///
IRR_PIVOTDROP IRR_SPRINKLER IRR_PIVOTFLOOD IRR_DRIPOTHER IRR_OTHER ///
TEN_MILE FIVE_MILE postLEMA LEMA_EFFECT [aweight=ACRES_IRR], ///
        by(WUA_YEAR WR_ID WUAPERS_ID TACRES_IRR NACRES_IRR)
```

```
sort WR_ID WUA_YEAR
gen APPLIED_INCH = (AF_USED*12)
gen INTENSITY = (APPLIED_INCH/ACRES_IRR)
duplicates report WR_ID WUA_YEAR
duplicates drop WR_ID WUA_YEAR, force
merge 1:m WUA_YEAR WR_ID using "..\Water_Use_WEATHER_WR.dta", ///
keep(match)
collapse (rawsum) AF_USED ACRES_IRR (mean) ALFALFA CORN SORGHUM SOYBEAN ///
WHEAT MULTIPLE_UNKNOWN OTHER_CROP IRR_FLOOD IRR_DRIP IRR_PIVOT ///
IRR_PIVOTDROP IRR_SPRINKLER IRR_PIVOTFLOOD IRR_DRIPOTHER IRR_OTHER ///

TEN_MILE FIVE_MILE postLEMA LEMA_EFFECT ppt ET0[aweight=ACRES_IRR], ///
        by(WUA_YEAR WR_ID WUAPERS_ID TACRES_IRR NACRES_IRR)
sort WR_ID WUA_YEAR
gen APPLIED_INCH = (AF_USED*12)
gen INTENSITY = (APPLIED_INCH/ACRES_IRR)
duplicates report WR_ID WUA_YEAR

*Final 10 Mile Dataset for Analysis (Dataset 5)

*********************************************
save "..\DID_10MILE_Dataset.dta", replace
clear
*********************************************

*Fixed Effects Model at the Extensive and Intensive Margins

use "..\DID_10MILE_Dataset.dta"
xtset WR_ID WUA_YEAR, yearly

gen lnAPPLIED_INCH=ln(APPLIED_INCH)
gen lnACRES_IRR=ln(ACRES_IRR)
gen lnINTENSITY=ln(INTENSITY)

egen f = group(WUAPERS_ID)
egen FARMER = group(WUAPERS_ID WUA_YEAR)
sort f
set matsize 1500
set emptycells drop

* Total Extensive Margin
xtreg lnACRES_IRR LEMA_EFFECT ppt ET0 i.FARMER i.WUA_YEAR, ///
fe vce(cluster WR_ID)
*Apply Log-Linear Correction
nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
estimates store EXTENSIVE

* Total Intensive Margin
xtreg lnINTENSITY LEMA_EFFECT ppt ET0 i.FARMER i.WUA_YEAR, ///
fe vce(cluster WR_ID)
*Apply Log-Linear Correction
nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
estimates store INTENSIVE

* Direct Intensive Margin (Crop Controls)
xtreg lnINTENSITY LEMA_EFFECT ALFALFA CORN SORGHUM SOYBEAN WHEAT ppt ET0 ///
i.FARMER i.WUA_YEAR, fe vce(cluster WR_ID)
*Apply Log-Linear Correction
nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
estimates store INTENSIVE_DIRECT_1

* Direct Intensive Margin (Crop and System Controls)
xtreg lnINTENSITY LEMA_EFFECT ALFALFA CORN SORGHUM SOYBEAN ///
WHEAT IRR_FLOOD IRR_DRIP IRR_PIVOT IRR_PIVOTDROP IRR_SPRINKLER ppt ET0 ///
IRR_PIVOTFLOOD IRR_DRIPOTHER IRR_OTHER ///
i.FARMER i.WUA_YEAR, fe vce(cluster WR_ID)
*Apply Log-Linear Correction
nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
estimates store INTENSIVE_DIRECT_2
```

```
        estimates table EXTENSIVE INTENSIVE INTENSIVE_DIRECT_1 ///
        INTENSIVE_DIRECT_2,star stats(N r2 r2_a)

        *Total Marginal Effect
        xtreg lnAPPLIED_INCH LEMA_EFFECT i.FARMER i.WUA_YEAR ppt ET0, ///
        fe vce(cluster WR_ID)
        *Apply Log-Linear Correction
        nlcom ((exp(_b[LEMA_EFFECT]))-1)*100
estimates store TOTAL

        *False LEMA effect in 2011
        clear
        set more off

        use "..\DID_LEMA_Dataset_WEATHER_WR.dta" //(Dataset 4)
        xtset WR_ID WUA_YEAR, yearly
        keep if WUA_YEAR<=2012

        gen postFALSE = 0
        replace postFALSE = 1 if WUA_YEAR >= 2011
        generate FALSE_EFFECT = postFALSE*LEMA

        gen lnAPPLIED_INCH=ln(APPLIED_INCH)
        gen lnACRES_IRR=ln(ACRES_IRR)
        gen lnINTENSITY=ln(INTENSITY)

        egen f = group(WUAPERS_ID)
        egen FARMER = group(WUAPERS_ID WUA_YEAR)
        sort f
        set matsize 1500
        set emptycells drop
        sort WUA_YEAR

        xtreg lnAPPLIED_INCH FALSE_EFFECT i.FARMER i.WUA_YEAR ppt ET0, ///
        fe vce(cluster WR_ID)
        *Apply Log-Linear Correction
        nlcom ((exp(_b[FALSE_EFFECT]))-1)*100
        estimates store APPLIED_2

        xtreg lnACRES_IRR FALSE_EFFECT i.FARMER i.WUA_YEAR ppt ET0, ///
        fe vce(cluster WR_ID)
        *Apply Log-Linear Correction
        nlcom ((exp(_b[FALSE_EFFECT]))-1)*100
        estimates store ACRES_2

        xtreg lnINTENSITY FALSE_EFFECT i.FARMER i.WUA_YEAR ppt ET0, ///
        fe vce(cluster WR_ID)
        *Apply Log-Linear Correction
        nlcom ((exp(_b[FALSE_EFFECT]))-1)*100
        estimates store INTENSITY_2

        xtreg lnINTENSITY FALSE_EFFECT ALFALFA CORN SORGHUM SOYBEAN WHEAT ///
        i.FARMER i.WUA_YEAR ppt ET0, ///
        fe vce(cluster WR_ID)
        *Apply Log-Linear Correction
        nlcom ((exp(_b[FALSE_EFFECT]))-1)*100
        estimates store INTENSITY_22

        estimates table APPLIED_2 ACRES_2 INTENSITY_2 INTENSITY_22,
        star stats(N r2 r2_a)

****************************************************
* Bootstrap standard errors were estimated on server
****************************************************

log close

********************************************************************************
********************************************************************************
    ***Analysis of the Sheridan 6 LEMA inside/outside 5 Mile D-I-D Model***
```

```
     ****************Ch6: Estimates of Effects on Inputs******************
*******************************************************************************
///////////////////////////////////////////////////////////////////////////////
clear
set more off
capture log close
log using "DID_INPUTS.txt", text replace

*******************************************************************************
                         //INPUT EXPENDITURES//
*******************************************************************************
//Step 1: Bring in Table of Estimated Input Expenditures
import excel "../DID_INPUTS/Input Expenditure Table by Crop Type.xlsx", ///
sheet("Sheet1") firstrow

*Final Input Expenditure dataset (Dataset 6)

            ***************************************************
             save "../DID_INPUTS/DID_INPUTS.dta", replace clear
            ***************************************************


                                    //Input Expenditures//
//      Crop Type     Fertilizer    Herbicide  Insecticide    Seed    Bushels
//      Corn          84.18         48.95      14.57          113.92  225.00
//      Soybeans      18.83         34.95                     55.50   60.00
//      Wheat         38.74         6.31                      18.00   65.00
//      Sorghum       60.93         41.25                     14.92   160.00
//      Other         49.84         23.78                     16.46   112.50

*******************************************************************************
                                //ANALYSIS//
*******************************************************************************

clear
use "..\DID_LEMA_Dataset_WEATHER_WR.dta" //(Dataset 4)
        xtset WR_ID WUA_YEAR, yearly
        keep if WUA_YEAR>=2009
        xtdescribe

//Step 1: Generate Input Price Variables

        gen FERTILIZER = 0
        replace FERTILIZER = 84.18      if CORN == 1
        replace FERTILIZER = 18.83      if SOYBEAN == 1
        replace FERTILIZER = 38.74  if WHEAT == 1
        replace FERTILIZER = 41.25  if SORGHUM == 1
        replace FERTILIZER = 23.78  if OTHER_CROP == 1

        gen HERBICIDE = 0
        replace HERBICIDE = 48.95       if CORN == 1
        replace HERBICIDE = 34.95       if SOYBEAN == 1
        replace HERBICIDE = 6.31        if WHEAT == 1
        replace HERBICIDE = 60.93       if SORGHUM == 1
        replace HERBICIDE = 49.84       if OTHER_CROP == 1

        gen INSECTICIDE
        replace INSECTICIDE = 14.5      if CORN == 1
        replace INSECTICIDE = 0         if SOYBEAN == 1
        replace INSECTICIDE = 0         if WHEAT == 1
        replace INSECTICIDE = 0         if SORGHUM == 1
        replace INSECTICIDE = 0         if OTHER_CROP == 1

        gen SEED = 0
       replace SEED = 113.92            if CORN == 1
       replace SEED = 55.50             if SOYBEAN == 1
       replace SEED = 18.00             if WHEAT == 1
       replace SEED = 14.92             if SORGHUM == 1
       replace SEED = 16.46             if OTHER_CROP == 1

//Step 2: Generate Share Input Variables
```

```
*Total FERTILIZER EXPENDITURE
         gen CORN_FERTILIZER = CORN*FERTILIZER
         gen SOYBEAN_FERTILIZER = SOYBEAN*FERTILIZER gen
         WHEAT_FERTILIZER = WHEAT*FERTILIZER
         gen SORGHUM_FERTILIZER = SORGHUM*FERTILIZER
         gen ALFALFA_FERTILIZER = OTHER_CROP*FERTILIZER
         gen OTHER_CROP_FERTILIZER = OTHER_CROP*FERTILIZER

*Total HERBICIDE EXPENDITURE
         gen CORN_HERBICIDE = CORN*HERBICIDE
         gen SOYBEAN_HERBICIDE = SOYBEAN*HERBICIDE gen
         WHEAT_HERBICIDE = WHEAT*HERBICIDE
         gen SORGHUM_HERBICIDE = SORGHUM*HERBICIDE
         gen ALFALFA_HERBICIDE = OTHER_CROP*HERBICIDE
         gen OTHER_CROP_HERBICIDE = OTHER_CROP*HERBICIDE


*Total INSECTICIDE EXPENDITURE
         gen CORN_INSECTICIDE = CORN*INSECTICIDE
         gen SOYBEAN_INSECTICIDE = SOYBEAN*INSECTICIDE gen
         WHEAT_INSECTICIDE = WHEAT*INSECTICIDE
         gen SORGHUM_INSECTICIDE = SORGHUM*INSECTICIDE
         gen ALFALFA_INSECTICIDE = OTHER_CROP*INSECTICIDE
         gen OTHER_CROP_INSECTICIDE = OTHER_CROP*INSECTICIDE

*Total SEED EXPENDITURE
         gen CORN_SEED = CORN*SEED
         gen SOYBEAN_SEED = SOYBEAN*SEED gen WHEAT_SEED
         = WHEAT*SEED
         gen SORGHUM_SEED = SORGHUM*SEED
         gen ALFALFA_SEED = OTHER_CROP*SEED
         gen OTHER_CROP_SEED = OTHER_CROP*SEED



         *Final Acreage Input Expenditure dataset (Dataset 7)

 save "..\DID_LEMA_Dataset_WEATHER_WR_INPUTS.dta", replace clear

 ********************************************************************************
                                       //Analysis//
 ********************************************************************************  clear
 use "..\DID_LEMA_Dataset_WEATHER_WR_INPUTS.dta" //(Dataset 7) xtset WR_ID
         WUA_YEAR, yearly
         keep if WUA_YEAR>=2009 xtdescribe

 //Step 3: Visual Analysis (D-I-D) of Share of Acreage Changes
 **Share Acres**
 *CORN

mean CORN   if WUA_YEAR <= 2012 and LEMA == 1
mean CORN   if WUA_YEAR >  2012 and LEMA == 1
mean CORN   if WUA_YEAR <= 2012 and LEMA == 0
mean CORN   if WUA_YEAR >  2012 and LEMA == 0


*SOYBEAN
mean SOYBEAN if WUA_YEAR <= 2012 and LEMA == 1
mean SOYBEAN if WUA_YEAR >  2012 and LEMA == 1
mean SOYBEAN if WUA_YEAR <= 2012 and LEMA == 0
mean SOYBEAN  if WUA_YEAR >  2012 and LEMA == 0


*WHEAT
mean WHEAT  if WUA_YEAR <= 2012 and LEMA == 1
mean WHEAT  if WUA_YEAR >  2012 and LEMA == 1
mean WHEAT  if WUA_YEAR <= 2012 and LEMA == 0
mean WHEAT  if WUA_YEAR >  2012 and LEMA == 0
```

```
*SORGHUM
mean SORGHUM if WUA_YEAR <= 2012 and LEMA == 1
mean SORGHUM if WUA_YEAR >  2012 and LEMA == 1
mean SORGHUM if WUA_YEAR <= 2012 and LEMA == 0
mean SORGHUM if WUA_YEAR >  2012 and LEMA == 0

*ALFALFA
mean ALFALFA if WUA_YEAR <= 2012 and LEMA == 1
mean ALFALFA if WUA_YEAR >  2012 and LEMA == 1
mean ALFALFA if WUA_YEAR <= 2012 and LEMA == 0
mean ALFALFA if WUA_YEAR >  2012 and LEMA == 0

*OTHER
mean OTHER_CROP if WUA_YEAR <= 2012 and LEMA == 1
mean OTHER_CROP if WUA_YEAR >  2012 and LEMA == 1
mean OTHER_CROP if WUA_YEAR <= 2012 and LEMA == 0
mean OTHER_CROP if WUA_YEAR >  2012 and LEMA == 0

 *Generate Farmer-Time Specific Variables

         egen f = group(WUAPERS_ID)
         egen FARMER = group(WUAPERS_ID WUA_YEAR) sort f
         set matsize 1500
         set emptycells drop

 * Share Effects

         *CORN
         xtreg CORN LEMA_EFFECT ppt ET0 i.FARMER i.WUA_YEAR, /// fe vce(cluster
         WR_ID)
         summarize CORN_FERTILIZER CORN_HERBICIDE CORN_INSECTICIDE CORN_SEED

         *SOYBEAN
         xtreg SOYBEAN LEMA_EFFECT ppt ET0 i.FARMER i.WUA_YEAR, ///
         fe vce(cluster WR_ID)
         summarize SOYBEAN_FERTILIZER SOYBEAN_HERBICIDE /// SOYBEAN_SEED

         *WHEAT
         xtreg WHEAT LEMA_EFFECT ppt ET0 i.FARMER i.WUA_YEAR, /// fe
         vce(cluster WR_ID)
         summarize WHEAT_FERTILIZER WHEAT_HERBICIDE WHEAT_INSECTICIDE WHEAT_SEED


         *SORGHUM
         xtreg SORGHUM LEMA_EFFECT ppt ET0 i.FARMER i.WUA_YEAR, ///
         fe vce(cluster WR_ID)
         summarize SORGHUM_FERTILIZER SORGHUM_HERBICIDE SORGHUM_INSECTICIDE /// SORGHUM_SEED

         *ALFALFA
         xtreg ALFALFA LEMA_EFFECT ppt ET0 i.FARMER i.WUA_YEAR, ///
         fe vce(cluster WR_ID)
         summarize ALFALFA_FERTILIZER ALFALFA_HERBICIDE ALFALFA_INSECTICIDE /// ALFALFA_SEED

         *OTHER
         xtreg OTHER_CROP LEMA_EFFECT ppt ET0 i.FARMER i.WUA_YEAR, ///
         fe vce(cluster WR_ID)
         summarize OTHER_CROP_FERTILIZER OTHER_CROP_HERBICIDE ///
         OTHER_CROP_INSECTICIDE OTHER_CROP_SEED

 * No farmer-time fixed effects

         *CORN
         xtreg CORN LEMA_EFFECT ppt ET0 i.WUA_YEAR, /// fe
         vce(cluster WR_ID)
         summarize CORN_FERTILIZER CORN_HERBICIDE CORN_INSECTICIDE CORN_SEED

         *SOYBEAN
         xtreg SOYBEAN LEMA_EFFECT ppt ET0 i.WUA_YEAR, /// fe vce(cluster
         WR_ID)
```

```
        summarize SOYBEAN_FERTILIZER SOYBEAN_HERBICIDE /// SOYBEAN_SEED

        *WHEAT
        xtreg WHEAT LEMA_EFFECT ppt ET0 i.WUA_YEAR, /// fe vce(cluster
        WR_ID)
        summarize WHEAT_FERTILIZER WHEAT_HERBICIDE WHEAT_INSECTICIDE WHEAT_SEED

        *SORGHUM
        xtreg SORGHUM LEMA_EFFECT ppt ET0 i.WUA_YEAR, /// fe vce(cluster
        WR_ID)
        summarize SORGHUM_FERTILIZER SORGHUM_HERBICIDE SORGHUM_INSECTICIDE /// SORGHUM_SEED

        *ALFALFA
        xtreg ALFALFA LEMA_EFFECT ppt ET0 i.WUA_YEAR, /// fe vce(cluster WR_ID)
        summarize ALFALFA_FERTILIZER ALFALFA_HERBICIDE ALFALFA_INSECTICIDE /// ALFALFA_SEED

        *OTHER
        xtreg OTHER_CROP LEMA_EFFECT ppt ET0 i.WUA_YEAR, /// fe vce(cluster
        WR_ID)
        summarize OTHER_CROP_FERTILIZER OTHER_CROP_HERBICIDE ///
        OTHER_CROP_INSECTICIDE OTHER_CROP_SEED


log close

********************************************************************************
           ***Analysis of the Sheridan 6 LEMA inside/outside 5 Mile D-I-D Model***
           ****************Ch8: Estimates of Effects on Yields******************
********************************************************************************
////////////////////////////////////////////////////////////////////////////////  clear
set more off capture log close
log using "DID_YIELDS.txt", text replace
********************************************************************************
                          //ESTIMATE NONLINEAR FUNCTIONS//
********************************************************************************

//Step 1: Import Stone Yield Simulation Data

*CORN
import delimited "..\DID_YIELDS\CORN_STONE.csv", clear //(Dataset 8) reg yield
c.netirrigationin##c.netirrigationin c.precip##c.precip c.netirrigationin#c.precip
predict yield_hat

twoway (scatter yield netirrigationin ) ///
        (line yield_hat netirrigationin if precip==11) /// (line yield_hat
        netirrigationin   if   precip==12)   ///   (line   yield_hat
        netirrigationin   if   precip==13)   ///   (line   yield_hat
        netirrigationin   if   precip==14)   ///   (line   yield_hat
        netirrigationin   if   precip==15)   ///   (line   yield_hat
        netirrigationin   if   precip==16)   ///   (line   yield_hat
        netirrigationin   if   precip==17)   ///   (line   yield_hat
        netirrigationin   if   precip==18)   ///   (line   yield_hat
        netirrigationin   if   precip==19)   ///   (line   yield_hat
        netirrigationin if precip==20) ///
        (line yield_hat netirrigationin if precip==21), legend(off) /// xtitle("Net
        Irrigation (in)") ytitle("Corn Yield (bu/acre)") graphregion(color(white))

graph export "corn_yield_function.png", replace

* Show regression lines outside of original data replace precip=24
if precip==11
replace  precip=27  if  precip==12  replace
precip=31 if precip==13 drop if precip<=21
drop yield_hat predict yield_hat
twoway (line yield_hat netirrigationin if precip==24) /// (line
        yield_hat netirrigationin if precip==27) ///
        (line yield_hat netirrigationin if precip==31), legend(off) /// xtitle("Net
        Irrigation (in)") ytitle("Corn Yield (bu/acre)")

clear
```

```
use "..\DID_LEMA_Dataset_WEATHER_WR.dta", clear //(Dataset 4) xtset WR_ID
        WUA_YEAR, yearly
        keep if WUA_YEAR>=2009
* Net Irrigation is the Intensity times the efficiency gen
netirrigationin=INTENSITY*0.9
* Rename preciptitation so that it matches yield regression ren ppt
precip

predict CORN_YIELD if CORN==1 summ
CORN_YIELD, detail

scatter CORN_YIELD INTENSITY if CORN==1
* drop outliers
summ INTENSITY if CORN==1, detail drop if
INTENSITY>28 and CORN==1
scatter CORN_YIELD INTENSITY if CORN==1

save "..\DID_YIELDS\DID_LEMA_Dataset_WEATHER_WR_YIELDS.dta", replace


*SOYBEAN
import delimited "..\DID_YIELDS\SOYBEAN_STONE.csv", clear
reg yield c.netirrigationin##c.netirrigationin c.precip##c.precip
c.netirrigationin#c.precip
predict yield_hat

twoway (scatter yield netirrigationin ) ///
        (line yield_hat netirrigationin if precip==11) /// (line yield_hat
        netirrigationin    if    precip==12)    ///    (line    yield_hat
        netirrigationin    if    precip==13)    ///    (line    yield_hat
        netirrigationin    if    precip==14)    ///    (line    yield_hat
        netirrigationin    if    precip==15)    ///    (line    yield_hat
        netirrigationin    if    precip==16)    ///    (line    yield_hat
        netirrigationin    if    precip==17)    ///    (line    yield_hat
        netirrigationin    if    precip==18)    ///    (line    yield_hat
        netirrigationin    if    precip==19)    ///    (line    yield_hat
        netirrigationin if precip==20) ///
        (line yield_hat netirrigationin if precip==21), legend(off) /// xtitle("Net
        Irrigation (in)") ytitle("Soybean Yield (bu/acre)") graphregion(color(white))

graph export "soybean_yield_function.png", replace

* Show regression lines outside of original data replace precip=24
if precip==11
replace  precip=27  if  precip==12  replace
precip=31 if precip==13 drop if precip<=21
drop yield_hat predict yield_hat
twoway (line yield_hat netirrigationin if precip==24) /// (line
        yield_hat netirrigationin if precip==27) ///
        (line yield_hat netirrigationin if precip==31), legend(off) /// xtitle("Net
        Irrigation (in)") ytitle("Soybean Yield (bu/acre)")

clear
use "..\DID_YIELDS\DID_LEMA_Dataset_WEATHER_WR_YIELDS.dta"

predict SOYBEAN_YIELD if SOYBEAN==1 summ
SOYBEAN_YIELD, detail

scatter SOYBEAN_YIELD INTENSITY if SOYBEAN==1
* drop outliers
summ INTENSITY if SOYBEAN==1, detail drop if
INTENSITY>24 and SOYBEAN==1
scatter SOYBEAN_YIELD INTENSITY if SOYBEAN==1

*Final Water Use Yield Dataset (Dataset 9)

        ******************************************************
        save "..\DID_YIELDS\DID_LEMA_Dataset_WEATHER_WR_YIELDS.dta", replace
        ******************************************************

********************************************************************************
```

```
                                //ANALYSIS//
 ********************************************************************************

 clear
 use "..\DID_YIELDS\DID_LEMA_Dataset_WEATHER_WR_YIELDS.dta" //(Dataset 9)  xtset WR_ID
         WUA_YEAR, yearly
         keep if WUA_YEAR>=2009 xtdescribe

         gen ln_CORN_YIELD=ln(CORN_YIELD)
         gen ln_SOYBEAN_YIELD=ln(SOYBEAN_YIELD)

 //Step 1: Visual Analysis (D-I-D)

*CORN
mean CORN_YIELD  if WUA_YEAR <= 2012 and LEMA == 1
mean CORN_YIELD  if WUA_YEAR >  2012 and LEMA == 1
mean CORN_YIELD  if WUA_YEAR <= 2012 and LEMA == 0
mean CORN_YIELD  if WUA_YEAR >  2012 and LEMA == 0

*SOYBEAN
mean SOYBEAN_YIELD  if WUA_YEAR <= 2012 and LEMA == 1
mean SOYBEAN_YIELD  if WUA_YEAR >  2012 and LEMA == 1
mean SOYBEAN_YIELD  if WUA_YEAR <= 2012 and LEMA == 0
mean SOYBEAN_YIELD   if WUA_YEAR >  2012 and LEMA == 0

*Generate Farmer-Time Specific Variables
egen f = group(WUAPERS_ID)
egen FARMER = group(WUAPERS_ID WUA_YEAR) sort f
set matsize 1500
set emptycells drop

* Total Effects
xtreg ln_CORN_YIELD LEMA_EFFECT precip ET0 i.FARMER i.WUA_YEAR, /// fe vce(cluster WR_ID)
*Apply Log-Linear Correction
nlcom ((exp(_b[LEMA_EFFECT]))-1)*100

xtreg ln_SOYBEAN_YIELD LEMA_EFFECT precip ET0 i.FARMER i.WUA_YEAR, /// fe vce(cluster WR_ID)

*Apply Log-Linear Correction
nlcom ((exp(_b[LEMA_EFFECT]))-1)*100

* No farmer-time fixed effects
xtreg ln_CORN_YIELD LEMA_EFFECT precip ET0 i.WUA_YEAR, /// fe vce(cluster WR_ID)

*Apply Log-Linear Correction
nlcom ((exp(_b[LEMA_EFFECT]))-1)*100

xtreg ln_SOYBEAN_YIELD LEMA_EFFECT precip ET0 i.WUA_YEAR, /// fe vce(cluster WR_ID)
        *Apply Log-Linear Correction
        nlcom ((exp(_b[LEMA_EFFECT]))-1)*100  log close
////////////////////////////////////////////////////////////////////////
*******************************END OF CODE*****************************
```