Essays on the economics of groundwater depletion and management in irrigated agriculture

by

Gabriela Perez-Quesada

B.A., University of Republic Uruguay, 2012

M.A., University of Republic Uruguay, 2017

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the
requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
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Abstract

The depletion of groundwater stocks reduces the flow of economic value and the production of goods from the resource. This dissertation quantifies these effects in the context of the High Plains Aquifer in the central US. One particular challenge in estimating these effects that we overcome is that feedback effects from irrigation behavior affect resource conditions, which creates an endogeneity concern. We also provide new insights on the potential of collective efforts by irrigators to manage the resource. We study how heterogeneity in resource and user characteristics affect their individuals' willingness to support efforts to collectively reduce water use.

The first chapter estimates how changes in groundwater stocks affect the returns to agricultural land. We avoid bias from feedback effects by exploiting hydrologic variation in pre-development saturated thickness that was determined by natural processes in previous geological eras. Simulation results reveal that the average annual present value of returns to land are expected to decrease in the High Plains region by $120.6 million in 2050, and by $250.5 million in 2100. The most severe decreases in returns to land are expected to occur in Texas, Kansas, and Colorado. When the initial saturated thickness is less than 70 feet, most of the economic impact (63%) of a decrease in the stock of groundwater occurs through an adjustment in irrigated acreage (extensive margin), while 37% occurs through reduced irrigated rental rates (intensive margin). When saturated thickness is larger, nearly all of the response is at the extensive margin.

The second chapter examines how observed differences in the stock of groundwater affect corn production. To account for the endogeneity of groundwater stock, we exploit variation in current saturated thickness due to variation in pre-development saturated thickness. Simulation results reveal that the annual production of corn would decrease by 48.1 million bushels in the north portion of the High Plains Aquifer due to a uniform 10 ft decrease in

saturated thickness, whereas the annual production of corn would decrease by 15.7 million bushels in the south. Further, we find that when initial saturated thickness is less than 70 ft, most of the impact on corn production of a decrease in the stock of groundwater occurs through an adjustment in irrigated acres in both the north and the south. When saturated thickness is larger than 70 ft, then the adjustment is mostly through a change in cropping patterns on irrigated land in the south but still through irrigated acres in the north.

The third chapter uses unique data obtained from consequential stated preference surveys in Kansas to explore the factors that influence farmers preferred reductions in groundwater use through a water conservation program implemented by a Groundwater Management District. Our results reveal that farmers located in areas where the aquifer is more depleted support larger reductions in groundwater use. But we also find that characteristics of the users matter as much or more than the status of the aquifer in determining support. Opposition to reductions in water use are strongest among farmers who strongly agree that water rights are a private property, landlords and those who irrigate a larger proportion of their farm. Further, we evaluate farmers' preferences for the methods of assigning water allocations. We find that none of the options are preferred by a majority of farmers and there is no clear evidence that aquifer characteristics or observed farmer characteristics are the key factors affecting the probability that a farmer ranks a method as the best option. This makes it difficult for groundwater managers to identify which method is more likely to be considered fair by farmers. Our results are informative for managers of water throughout Kansas, the High Plains and other regions where conserving water resources is a high priority and localized and stakeholder-driven conservation plans could be a solution.

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Nathan P. Hendricks

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Acknowledgments

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Chapter 1

The Economic Cost of Groundwater Depletion in the High Plains Aquifer

1.1 Introduction

Groundwater use for irrigation offers a substantial source of water to supplement insufficient growing season rainfall in semi-arid areas around the world. However, the extraction of groundwater for irrigation at rates greater than natural recharge has led to persistent aquifer depletion in many countries (Richey et al., 2015). Stressed aquifer conditions are especially important in the central and southern portion of the High Plains Aquifer (HPA) in the United States where water levels have been declining rapidly (Scanlon et al., 2012; Steward and Allen, 2016). While the change in groundwater stocks is relatively well established, there is much less evidence on the loss in economic value from the change in groundwater stocks.

Accurately estimating the economic value of the stock of groundwater is challenging for two main reasons. First, it is difficult to directly observe the marginal value of groundwater used for irrigation since the market for water is in general thin and has large frictions. Second, the existence of feedbacks across social and environmental dimensions of complex systems makes it difficult to support assumptions about excludability and the absence of interference required for causal inference (Ferraro et al., 2019). For example, current aquifer conditions depend on the behavior of users because as farmers increase groundwater extraction, the stock of groundwater decreases.

One approach to estimate the value of the stock of groundwater is to use revealed preference methods such as the hedonic price model, which obtains an implicit valuation of groundwater irrigation using information from well-functioning markets. As an example, the market value for irrigated and nonirrigated land provides information about the additional value created by groundwater used for irrigation. Hornbeck and Keskin (2014) find that aquifer access resulted in a \$25 billion increase in land values, while Sampson et al. (2019) find that agricultural land values are about 53% higher for irrigated parcels than similar nonirrigated parcels in the Kansas portion of the HPA. Yet these studies do not estimate the annual economic cost of a change in the stock of groundwater, which is a measure of key importance to stakeholders who are considering policies to address the depletion of groundwater.

Our paper quantifies the economic value of groundwater stocks using data on cash rental rates for irrigated versus nonirrigated land and the number of irrigated acres. We avoid bias from feedback effects by exploiting hydrologic variation in pre-development saturated thickness that is unrelated to irrigation behavior. Pre-development saturated thickness was determined by the structure and features of the pre-Ogallala surface roughly 5 to 24 million years ago, which led to variation in the availability of groundwater across the HPA today. Intuitively, our empirical strategy compares counties within the same state for a given year, with similar climatic, soil, and aquifer characteristics that have a different amount of current saturated thickness because of differences in pre-development saturated thickness. We investigate the use of county fixed effects but the results indicate that there is insufficient variability in saturated thickness remaining after including county fixed effects compared to the preferred specification.

Two-stage least square (2SLS) models of irrigated acres and irrigated cash rental rates on saturated thickness, controlling for other confounders are estimated. Pre-development saturated thickness is used as an instrument for current saturated thickness. The validity of the exclusion restriction is supported by conducting a falsification test to evaluate if pre-development saturated thickness is correlated with unobserved land productivity as reflected in nonirrigated rental rates. The parameter estimates are then used to simulate the economic impacts of projected aquifer depletion. The simulation results reveal that the average annual present value of returns to land are expected to decrease in the High Plains region by $120.6 million in 2050 and by $250.5 million in 2100. However, the economic impact of the projected decrease in saturated thickness varies significantly across regions of the HPA.

Our paper provides three main contributions. First, we estimate the economic value of groundwater stocks, rather than the value of access to groundwater. Measuring the value of the stock is important for estimating the economic value of different scenarios of resource depletion. For example, Hornbeck and Keskin (2014) compare land values in counties over the HPA aquifer with nearby similar counties to estimate the value of access to water. Edwards and Smith (2018) measure the effect of access to irrigation on land values throughout the entire western United States. Blakeslee et al. (2020) estimate the impact of groundwater access on various economic outcomes in India. One exception is that Sampson et al. (2019) estimate the effect of groundwater stocks on irrigated land values in Kansas. An advantage of our approach to using annual rental rates rather than land values is that annual rental rates do not reflect expectations of future changes in groundwater stocks.

The second contribution is that we use initial resource conditions as an instrument to reduce potential bias from feedback effects. Our approach is similar in spirit to Hornbeck and Keskin (2014) and Blakeslee et al. (2020) in that we exploit plausibly exogenous hydrologic variation. Hornbeck and Keskin (2014) utilize the plausibly exogenous boundary of the High Plains Aquifer. Blakeslee et al. (2020) compare households in India whose first borewell failed to those for whom it is still working within the same village. Blakeslee et al. (2020) argue that the failure of the first borewell is related to hydrologic factors that are exogenous to economic outcomes. However, our approach is different from these studies in that our approach allows us to estimate the value of groundwater stocks and not just access to groundwater. Our approach is also likely relevant to natural resources other than groundwater.

Third, we estimate the economic value of the stock of groundwater across the HPA region using observed irrigated acreage and rental market data. A large literature exists in hydrology that quantifies the extent of HPA depletion and projected aquifer conditions in the future, but without estimating economic impacts (Haacker et al., 2016; Scanlon et al., 2012; Steward et al., 2013). There is also a set of economic literature that uses programming models to simulate the economic impact of aquifer depletion, but is not validated with real-world data on farmer behavior (Ding and Peterson, 2012; Foster et al., 2017, 2015, 2014; Manning and Suter, 2019). Fenichel et al. (2016) model the value of natural capital with an application to groundwater stocks in Kansas, where the groundwater valuation model uses expenses from university crop budget and assumes that crop yields are not affected by groundwater stocks. Manning et al. (2020) use willingness to pay for well capacity from a contingent valuation survey to value groundwater stocks in an integrated assessment model. Our approach values groundwater stocks using rental market data and allows groundwater stocks to potentially affect irrigated acres, crop mix, and crop yield.

1.2 Background

The High Plains Aquifer (HPA) comprises 118.8 million acres over portions of eight states in the U.S.A: Colorado, Kansas, Nebraska, New Mexico, Oklahoma, South Dakota, Texas, and Wyoming (McGuire, 2017). It supplies over 30% of the total groundwater used for irrigation in the US (Steward et al., 2013), and it is the principal source of irrigation in a major agricultural producing region where crop yields are limited by precipitation (McGuire et al., 2003). However, the extraction of groundwater for irrigation at higher rates than natural recharge has led to persistent aquifer depletion, as in many other parts of the world (Richey et al., 2015; Scanlon et al., 2012; Steward and Allen, 2016)

A rapid and substantial increase in groundwater irrigation occurred after the adoption of center pivot technology during the 1960s. Estimated groundwater withdrawals increased from 4 to 19 million acre-feet between 1949 and 1974, while estimated irrigated acreage increased from 2.1 million acres in 1940 to 13.7 million acres in 1980 (McGuire et al., 2003). Water-level declines became evident in many areas of the HPA soon after this substantial increase in groundwater irrigation. By 1980, water levels had declined by more than 100 ft in portions of Kansas, New Mexico, Oklahoma, and Texas (McGuire et al., 2003). Depletion is much greater in the Central and Southern High Plains compared to depletion in the Northern portions. For instance, average water-level change from pre-development to 2015 ranged from a decline of 41.1 feet in Texas to a decline of only 0.9 feet in Nebraska (McGuire, 2017). In the period 2000 to 2020, the Central and Southern regions have shown a significant contraction in irrigated area attributable to increasingly scarce groundwater resources (Hrozencik and Aillery, 2021).

The saturated thickness is a measure of the vertical distance between the water table and the base of the aquifer, and thus reflects the resource stock. Current saturated thickness is influenced by pre-development saturated thickness, aquifer recharge, and extraction for irrigation. Pre-development saturated thickness is the estimated saturated thickness that existed before any effects imposed by human activity, and in our study, it is represented by a measure of saturated thickness in 1930[1]. The pre-development thickness of the Ogallala formation—the principal geologic unit of the HPA—was determined by the structure and features of the Ogallala geological setting formed roughly 5 to 24 million years ago, and the greatest thickness occurs where sediments have filled previously eroded drainage channels (NPGCD, 2021). Therefore, the pre-development saturated thickness was shaped by the structure of the pre-Ogallala surface that existed long before human settlement, so it is unrelated to human activity.

It is apparent in figure 1.1 that the geographic patterns of saturated thickness in 2017 resemble the pattern of pre-development saturated thickness in 1930. In general, the greatest contemporaneous saturated thickness occurs in those areas where the initial saturated thickness was also the largest.

[1] See Haacker et al. (2016) for more discussion on the pre-development date.

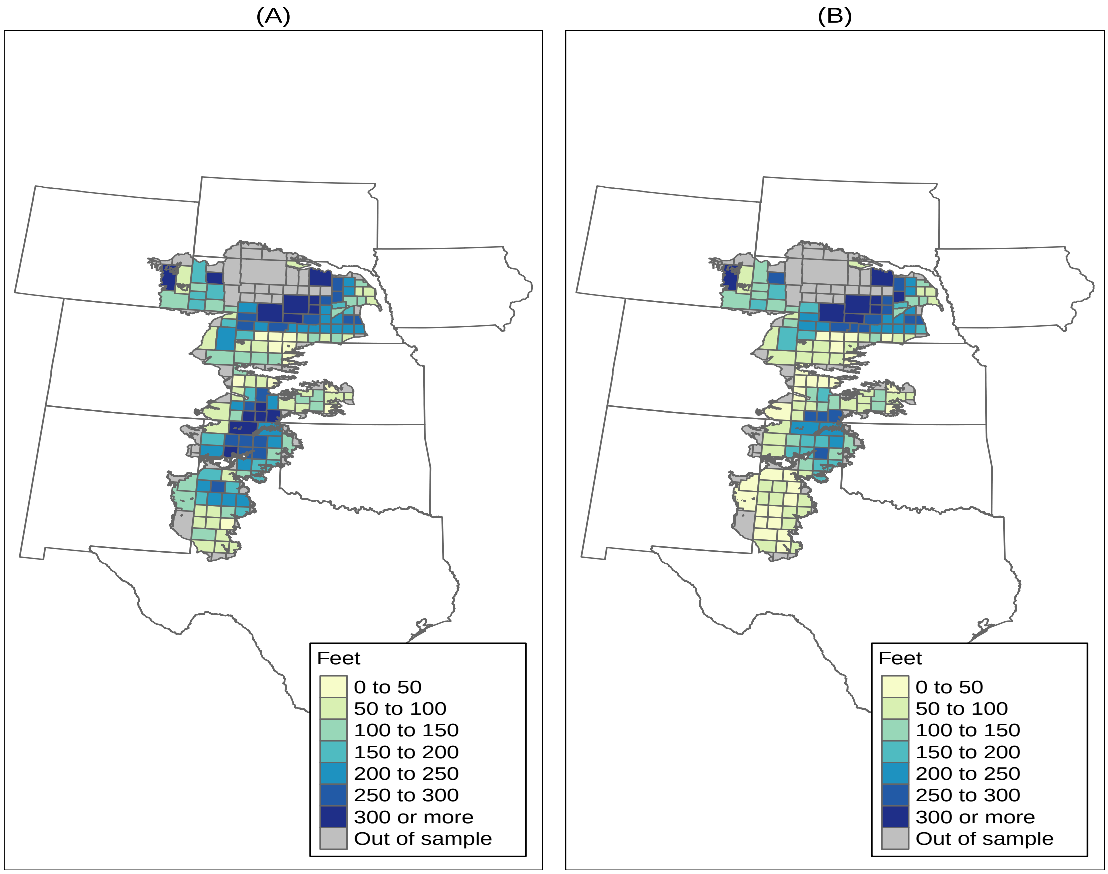

Figure 1.1: (A) Saturated thickness in 1930 (B) Saturated thickness 2017

The variability in current saturated thickness is also driven by variations in groundwater recharge from precipitation (Scanlon et al., 2012). Recharge is the natural movement of surficial water into an aquifer and is mainly determined by climate, soil, vegetation, land use, and depth to the water table (Sophocleous, 2005). The surficial rivers incise the Ogallala formation and hydrologicially separate the HPA into three units that are hydrologically disconnected. Much of the northern area of the aquifer consists of renewable groundwater formations with larger rates of recharge. The Central and Southern parts of the aquifer, however, consist primarily of nonrenewable or fossil groundwater with little recharge (Scanlon et al., 2012).

1.3 Conceptual Model

We explore the role of variation in groundwater stocks on irrigation decisions using saturated thickness information. Groundwater depletion affect farmers' economic benefits through two main mechanisms: decreasing well yields and increasing pumping costs. The well yield places an upper limit on the rate of groundwater extraction and is impacted by the saturated thickness and hydraulic conductivity. The cost of pumping increases with groundwater depletion since it requires more energy to pump the water from greater depths. We do not separately estimate these two different mechanisms, but instead we use reduced form models to estimate the overall impact of a change in saturated thickness.

The economic value of the stock of groundwater is reflected in the returns to land and modeled as

$$B_{it}(ST_{it}) = \Phi_{it}^{irr}(ST_{it})R_{it}^{irr}(ST_{it}) + (1 - \Phi_{it}^{irr}(ST_{it}) - \Phi_{it}^{past})R_{it}^{non} + \Phi_{it}^{past}R_{it}^{past},$$

where B_{it} is the return to land per acre of the county overlying the aquifer for county i in year t, Φ_{it}^{irr} is the proportion of acres in the county that are irrigated, Φ_{it}^{past} is the proportion of acres in the county that are pastureland, and $(1 - \Phi_{it}^{irr} - \Phi_{it}^{past})$ is the proportion of acres in the county that are nonirrigated. Economic variables R_{it}^{irr}, R_{it}^{non} and R_{it}^{past} are the irrigated, nonirrigated and pastureland cash rental rates, and ST_{it} is the saturated thickness.

We assume that when saturated thickness decreases, farmers switch to nonirrigated cropland as the next most productive use of land after irrigated cropland. Consequently, the extensive margin response may be underestimated if some farms convert from irrigated cropland to pasture. Deines et al. (2020) estimate that 87% of lost irrigated area through 2100 could support nonirrigated crop production and 13% was better suited to pasture use. In areas where farms switch to pasture rather than nonirrigated cropland, the rental rate of nonirrigated cropland is likely similar to the rental rate for pasture. Therefore, the assumption that irrigated cropland converts to nonirrigated cropland rather than pasture is a reasonable assumption for our study area.

A change in returns to land due to an exogenous change in saturated thickness is separated into two components:

$$\frac{\partial B_{it}}{\partial ST_{it}} = \underbrace{\frac{\partial \Phi_{it}^{irr}}{\partial ST_{it}}(R_{it}^{irr} - R_{it}^{non})}_{\textbf{Extensive Margin}} + \underbrace{\frac{\partial R_{it}^{irr}}{\partial ST_{it}}\Phi_{it}^{irr}}_{\textbf{Intensive Margin}},$$

since farmers may respond to increased water scarcity along adjustments in the extensive and intensive margins. Farmers are assumed to maximize their utility subject to the constraint that well yield imposes on instantaneous application rates (Foster et al., 2014). When saturated thickness is above a certain level, well yield is not a binding constraint and different levels of saturated thickness may have minimal impact on producer behavior. But for lower saturated thickness where well yields become constraining, farmers adjust their behavior through the extensive or intensive margins. On the extensive margin, the farmer decides what proportion of the field to plant with nonirrigated and irrigated crops. The intensive margin response captures two main adjustments: a reduction in water intensity for the proportion of the field that is irrigated that could affect crop yield, and a switch from relatively water intensive crops (e.g., corn) towards less water-intensive crops (e.g., wheat). The latter two adjustments will be reflected in farmers paying lower rental rates for irrigated land.

The objective of our empirical model is to estimate the nonlinear functions in saturated thickness of $\Phi_{it}^{irr}(ST_{it})$ and $R_{it}^{irr}(ST_{it})$ controlling for other explanatory variables, and then use the parameter estimates to simulate the economic impact of different scenarios of aquifer depletion. We allow a nonlinear relationship between saturated thickness on the output of interest based on recent studies where declines in well yield may have negative nonlinear impacts on irrigated area. Foster et al. (2014) and Foster et al. (2015) predict large reductions in irrigated area when well yield is limiting due to intraseasonal groundwater supply constraints.

Data is not directly available on depth to water table—the vertical distance from the land surface to water table—to explicitly control for differences in the cost of pumping. Instead, since saturated thickness and depth to water table are highly directly correlated, the estimated impact of saturated thickness on the outputs reflects the total impact of depletion through changes in well yields and cost of pumping (Rouhi Rad et al., 2021). Furthermore, a large literature examines how pumping costs affect water use indicating that the price elasticity of irrigation water demand is, in general, inelastic (e.g., Hendricks and Peterson, 2012; Mieno and Brozović, 2017; Pfeiffer and Lin, 2014; Scheierling et al., 2006; Schoengold et al., 2006). Recent studies have also shown how reductions in well yield negatively impact economic outputs (e.g., Foster et al., 2017, 2015, 2014; Hrozencik et al., 2017; Manning and Suter, 2019; Peterson and Ding, 2005; Rouhi-Rad et al., 2020). In particular, Foster et al. (2015) suggest that well yield has larger impacts on irrigated production areas and profits than depth to groundwater and pumping costs.

1.4 Empirical Strategy

The objective of our econometric model is to estimate the impact of saturated thickness on irrigated acres and irrigated cash rental rates. Even after controlling for relevant confounders, our estimates are subject to potential bias from feedback effects between saturated thickness and irrigation behavior. The feedback effect is evident between irrigated acres and saturated thickness which would bias our estimates downward—as farmers expand irrigated acres, extraction of groundwater increases and saturated thickness decreases. Pre-development saturated thickness is used as an instrument to obtain a source of plausibly exogenous variation in saturated thickness.

1.4.1 Econometric Model

Two-stage least square (2SLS) models are estimated for irrigated acres and irrigated cash rental rates. The nonlinear relationship between saturated thickness on the output of interest is represented using linear spline regression which is a piecewise linear function that fits a line in each segment of the saturated thickness space defined by the knots while requiring continuity at the knot (Harrell, 2001).

The second-stage equation is:

$$Y_{it} = \beta_0 + \beta_1[(1 - D_{it})ST_{it} + D_{it}K] + \beta_2 D_{it}(ST_{it} - K) + \alpha X_{it} + \delta_g + \gamma_{rt} + \varepsilon_{it}, \tag{1.1}$$

where K is the location of spline knot, and

$$D_{it} = \begin{cases} 0 & \text{if } ST_{it} < K \\ 1 & \text{if } ST_{it} \geq K. \end{cases}$$

The variable Y_{it} reflects either the percentage of acres irrigated of the total county area over the aquifer—note that we scale the dependent variable to $\Phi_{it}^{irr} \times 100$ for ease of interpreting marginal effects[2]—or the irrigated rental rate (R_{it}^{irr}) in county i at time t; ST_{it} is the average saturated thickness in the county; $[(1 - D_{it})ST_{it} + D_{it}K]$ and $D_{it}(ST_{it} - K)$ are linear spline functions of saturated thickness; X_{it} is a vector of controls (i.e., climatic variables, aquifer characteristics, and soil suitability for corn and soybeans); δ_g is the fraction of county area in each soil group; γ_{rt} are state-by-year fixed effects for state r and year t; and ε_{it} are idiosyncratic errors.

The coefficients of interest throughout the paper are β_1 and β_2. The estimated β_1 can be interpreted as the effect of saturated thickness on agricultural outcomes when the level of saturated thickness is less than K, while the estimated β_2 is the effect of saturated thickness on agricultural outcomes when the level of saturated thickness is greater than K. Based on exploratory analysis of our data and previous studies described above, we allow for one spline knot location ($K = 70$).

The linear spline functions of saturated thickness in equation 1.1 are treated as endoge-

[2]Even though our dependent variable (percentage of acres irrigated) is constrained to be between 0 and 100, we use a 2SLS model that treats the dependent variable as continuous since all values are in the interior (see table 1.1).

nous and, we use linear spline functions of pre-development saturated thickness as instruments. The first stage regressions are defined as:

$$[(1-D_{it})ST_{it}+D_{it}K]=\theta_0^1+\theta_1^1[(1-D_i^{'})ST1930_i+D_i^{'}K^{'}]+\theta_2^1D_i^{'}(ST1930_i-K^{'})+$$
$$+\phi^1X_{it}+\delta_g^1+\gamma_{rt}^1+v_{it}^1,$$

and

$$(ST_{it}-K)=\theta_0^2+\theta_1^2[(1-D_i^{'})ST1930_i+D_i^{'}K^{'}]+\theta_2^2D_i^{'}(ST1930_i-K^{'})+$$
$$+\phi^2X_{it}+\delta_g^2+\gamma_{rt}^2+v_{it}^2,$$

where $K^{'}$ is the spline knot and

$$D_i^{'}=\begin{cases}0 & \text{if } ST1930_i<K^{'}\\ 1 & \text{if } ST1930_i\geq K^{'}.\end{cases}$$

It is important to note that there are two endogenous explanatory variables ($[(1-D_{it})ST_{it}+D_{it}K]$ and $(ST_{it}-K)$), and our two instruments are $[(1-D_i^{'})ST1930_i+D_i^{'}K^{'}]$ and $D_i^{'}(ST1930_i-K^{'})$. The variable $ST1930_i$ is pre-development saturated thickness and the instruments, $[(1-D_i^{'})ST1930_i+D_i^{'}K^{'}]$ and $D_i^{'}(ST1930_i-K^{'})$, are linear spline functions of pre-development saturated thickness with $K^{'}=90$. Since pre-development saturated thickness is larger than current saturated thickness, the selected knot for the instrument is also larger.

For the statistical inference, the standard errors are clustered at the agricultural district level to adjust for heteroskedasticity, within-county correlation over time and spatial correlation between counties within a district. We follow Bester et al. (2011), who propose clustering by spatial groups as a simple and flexible method to account for spatial correlation, under the assumption that in most observations are far from borders and uncorrelated with observations in other groups. Bester et al. (2011) show that clustering results in valid inference if cluster-level averages are approximately independent.

1.4.2 Controlling for Potential Confounders

We explicitly include several variables to account for cross-sectional heterogeneity between counties in equation 1.1. Since the irrigated acreage information is based on the harvested acres, we include the contemporaneous cumulative measures for precipitation and reference evapotranspiration demand within the growing season (April 1 - September 30) to isolate contemporaneous weather effects. For example, drought conditions could induce some farmers to irrigate more acres than in previous years. We also include four long-run climate variables to describe the climate in each county: average precipitation, average reference evapotranspiration, the average number of growing degree days between 10°C and 30°C, and the average number of degree days greater than 32°C. This average number of growing degree days between 10°C and 30°C measures the exposure to heat within a range of temperatures considered beneficial to crop growth, and the average number of degree days greater than 32°C measures the exposure to heat levels that are detrimental to crop growth (Schlenker et al., 2006).

To account for the aquifer's characteristics in each county, we include three variables: hydraulic conductivity, specific yield and natural recharge. Hydraulic conductivity is a measure of the rate at which water can move laterally to a well, and specific yield is the volume of water per unit volume of aquifer that can be extracted by pumping. Where hydraulic conductivity and specific yield have higher values, we expect a reduction in pumping costs as water moves more readily to a well. Furthermore, hydraulic conductivity is also a measure of the shared nature of an aquifer. In regions with larger hydraulic conductivity, more water can be lost from a given well to the common pool, increasing the incentive to pump more water (Edwards, 2016). Natural recharge is the seepage of water into an aquifer, not including return flows from irrigation. It controls for changes in agricultural outcomes as a consequence of different expected rates of aquifer depletion that affect expectations of future aquifer stocks. Finally, to adjust for the effect of different soil characteristics on agricultural production, we control for major soil groups, and we also include a national commodity crop productivity index for corn and soybeans to account for the soil's suitability for corn and soybeans.

Our specification also includes state-by-year fixed effects to control for spatial-temporal variation, and allow for a separate effect for each possible combination of state and year. The state-by-year fixed effects absorb the effects of any arbitrary shock, including technological change, variation in commodity price and groundwater laws, which is specific to a state in any given year. For example, Nebraska uses correlative rights, and Kansas and Colorado both use prior appropriation rights, while in Texas groundwater is governed by the rule of capture. Intuitively, the empirical strategy compares counties within the same state for a given year, with similar climatic, soil, and aquifer characteristics that have a different amount of current saturated thickness caused by variation in pre-development saturated thickness. We also employ robustness tests in which we control for groundwater management districts-by-year fixed effects which show similar results to our preferred estimates.

To investigate the use of county fixed effects, we regress saturated thickness on various sets of fixed effects and then capture the standard deviation of the residuals which reflect the remaining saturated thickness variation (Fisher et al., 2012). The residual standard deviation of saturated thickness is equal to 102.4 when saturated thickness is regressed on an intercept, while it drops to 11.3 when county fixed effects are included. We also regress saturated thickness on all covariates and controls used in the main model specification, and the residual standard deviation of saturated thickness is equal to 68.3. These results indicate that there is insufficient variability in saturated thickness remaining after including county fixed effects compared to the preferred specification. Furthermore, we estimate our main model of interest including county fixed effects but the impact of saturated thickness on the outcomes is implausibly large (Table 1.6, section 1.6.4). Another justification for not including county fixed effects is that we need to find a new instrument because pre-development saturated thickness is invariant over time[3].

[3]The use of county fixed effects do not resolve the endogeneity from feedback effects since a change in irrigated acres affects the change in the stock of groundwater.

1.4.3 IV Assumptions

To identify β_1 and β_2 in the second stage (equation 1.1), the instruments must account for the saturated thickness variation. There is little doubt that the current saturated thickness is correlated with saturated thickness in 1930. As described in section 1.2, it is apparent that the geographic patterns of saturated thickness in 2017 resemble the pattern of pre-development saturated thickness in 1930 (figure 1.1). In general, the greatest contemporaneous saturated thickness occurs in those areas where initial saturated thickness was also the largest. Figure 1.2 provides a scatter plot of the relationship between pre-development saturated thickness and current saturated thickness. Again, this relationship shows that counties with low pre-development saturated thickness have substantially less saturated thickness today.

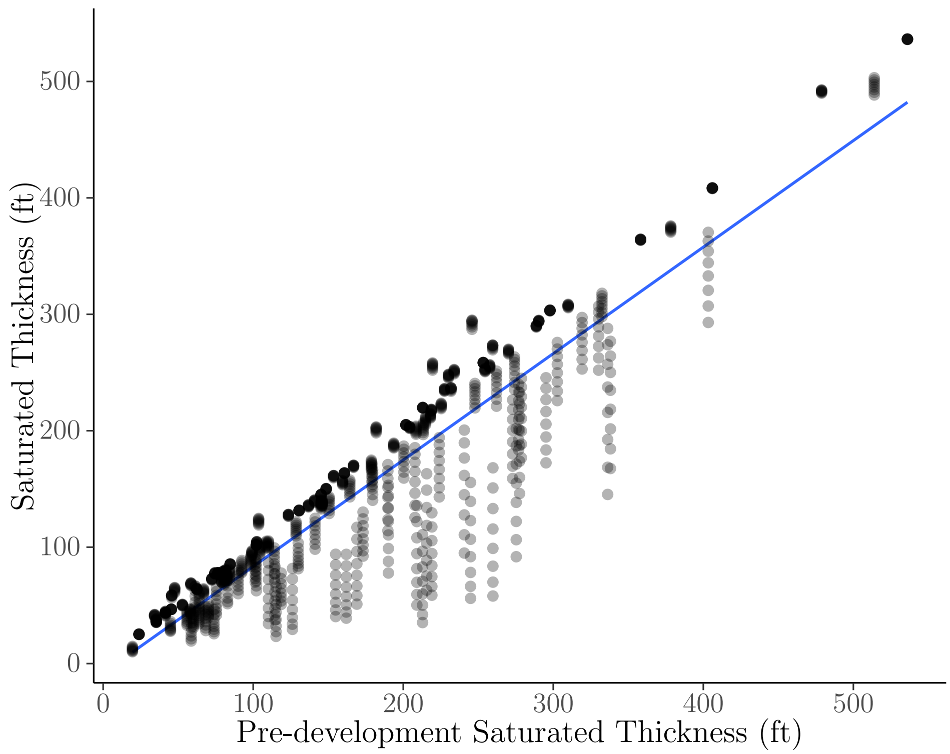

Figure 1.2: Relationship between pre-development saturated thickness and current saturated thickness

Identification also requires the exclusion restriction to be met. The exclusion restriction implied by our instrumental variable regression is that, conditional on the controls included in the regression, the pre-development saturated thickness has no effect on the percentage of acres irrigated or irrigated cash rents, other than its effect through the current saturated thickness. That is, unobservable effects that impact irrigated acres or irrigated rents are not correlated with variation in pre-development saturated thickness. Our exclusion restriction is plausible since, as explained in section 1.2, the pre-development saturated thickness was shaped by the structure and features of the Ogallala geological formations that existed long before human settlement, and so it is unrelated to human activity.

This exclusion restriction implies that pre-development saturated thickness is not spuriously correlated with productivity of the land today. In this case, the instrumental variable estimates may be assigning the effect of land productivity on outcomes to the effect of saturated thickness. This is unlikely to be the case since the ancient structure of the buried Ogallala geological formations has no inherent relationship with the agricultural productivity of the current land surface. Instead, the soil and climate controls are included in our models to address potential spurious correlations between pre-development saturated thickness and current land productivity, which affects irrigated acres and rents. Results from a falsification test are presented later to evaluate whether pre-development saturated thickness is correlated with unobserved land productivity.

1.5 Data and Study Area

Our study area includes 141 counties in six states overlying the HPA: Colorado, Kansas, Nebraska, New Mexico, Texas and Wyoming. We restrict the analysis to counties with a proportion of their total area over the aquifer greater than 60% to ensure the availability of groundwater for irrigation. The area of the sand hills in Nebraska overlies the aquifer but has minimal irrigation because the sandy soil makes the region unsuitable for crop farming (Peterson et al., 2016; USDA-NRCS, 2006). Therefore, we exclude from our analysis counties with greater than 55% of their total area in the sand hills. Table 1.1 shows summary statistics of the variables used in each econometric model. Next, we describe each source of data.

Irrigated areas at the county-level are available every five years from the US Census of Agriculture. We calculate the percentage of acres irrigated by dividing the irrigated acres by the total land area of the county overlying the aquifer. The empirical analysis of the extensive margin focuses on a balanced panel of 141 counties over the HPA from 1982 to 2017, resulting in a total of 1,128 observations. Annual data on irrigated cash rental rates for cropland at the county-level are obtained from the National Agricultural Statistics Service (NASS). These data are available from 2008 except for 2015 and 2018, and 2008 is excluded because the number of reported counties is small. In this case, the empirical analysis of the intensive margin focuses on an unbalanced panel of 141 counties over the HPA from 2009 to 2017, resulting in a total of 1,269 observations.

Table 1.1: Summary statistics for variables in the econometric analysis

	Extensive Margin Sample		Intensive Margin Sample	
Variables	Mean	Std. Dev.	Mean	Std. Dev.
Percentage of Acres Irrigated	18.34	15.41	–	–
Cash Irrigated Rent ($/acre)	–	–	151.64	69.58
Saturated Thickness (ft)	149.69	102.50	141.29	102.76
Growing Season Precipitation (in)	15.85	4.84	17.34	5.82
Growing Season Evapotranspiration (in)	34.46	2.89	34.79	3.41
Predevelopment Saturated Thickness (ft)	172.50	103.54	172.50	103.54
30-yr Avg. Precipitation (in)	16.31	3.10	16.31	3.10
30-yr Avg. Evapotranspiration (in)	34.56	2.60	34.56	2.60
30-yr Avg. Growing Degree Days (hundreds)	18.36	2.60	18.36	2.60
30-yr Avg. Extreme Degree Days	32.33	17.57	32.33	17.57
Hydraulic Conductivity (ft/day)	81.40	47.14	81.40	47.14
Specific Yield (fraction)	0.16	0.02	0.16	0.02
Natural Recharge (in)	2.62	2.13	2.62	2.13
Crop Productivity Index (fraction)	0.30	0.14	0.30	0.14
N	1,128		1,269	

Daily gridded weather data are obtained from PRISM and aggregated to the county level. We calculate the cumulative measure for precipitation and reference evapotranspiration demand within the growing season (April 1 - September 30) for each year. Reference evapotranspiration is a measure of the evaporative demand independent of crop characteristics and soil factors within a county. It is calculated using the reduced-set Penman-Monteith method following Hendricks (2018). We also construct four long-run climate variables: average precipitation, average reference evapotranspiration, the average number of degree days between 10° and 30°, and the average number of degree days greater than 32°. We calculate the cumulative measure for each of these four variables within the growing season (April 1 - September 30) for each year and then calculate the 30-year average (1987-2017).

Hydrologic characteristics of the HPA are obtained from two different sources. Pre-development saturated thickness, the average annual saturated thickness and the projected saturated thickness—values of saturated thickness up to 2100—are obtained from Steward and Allen (2016). Hydraulic conductivity, specific yield and natural recharge are obtained from the US Geological Survey. This hydraulic conductivity data set consists of contours and polygons that we aggregate to the county level (USGS, 1998). We use a raster of the average specific yield for the HPA and aggregate it to the county level (McGuire et al., 2012; USGS, 2012). Natural recharge data are also obtained from a raster and aggregated at county level (Houston et al., 2013; USGS, 2011). The average 2000-09 recharge is estimated by USGS using the Soil-Water Balance (SWB) model which assumes that irrigation systems are 100% efficient and there is no surplus irrigation water for recharge. Thus, natural recharge does not include return flows from irrigation (Stanton et al., 2011).

Major soil groups are obtained from Hornbeck and Keskin (2014). For example, soil groups appearing within the HPA include: alluvial, brown, chernozem, and chestnut[4]. The national commodity crop productivity index for corn and soybeans is obtained from the Soil Survey Geographic database (SSURGO). This variable ranges from 0.01 (low productivity) to 0.99 (high productivity). The maps in Figure 1.3 show the percentage of acres irrigated and irrigated rental rates in 2017. The spatial distributions of irrigated acres and irrigated rental rates appear to be related to the groundwater availability in the aquifer. In general, irrigated acres are largest in the north-east and decline moving south-west, where saturated thickness is lower and recharge from precipitation is less than groundwater demand for irrigation. Similarly, rental rates are largest in the Northern High Plains and decline moving south into the more arid region.

[4]A map can be found in the Hornbeck and Keskin (2014)'s online Appendix: `https://assets.aeaweb.org/asset-server/articles-attachments/aej/app/app/0601/2012-0256_app.pdf`

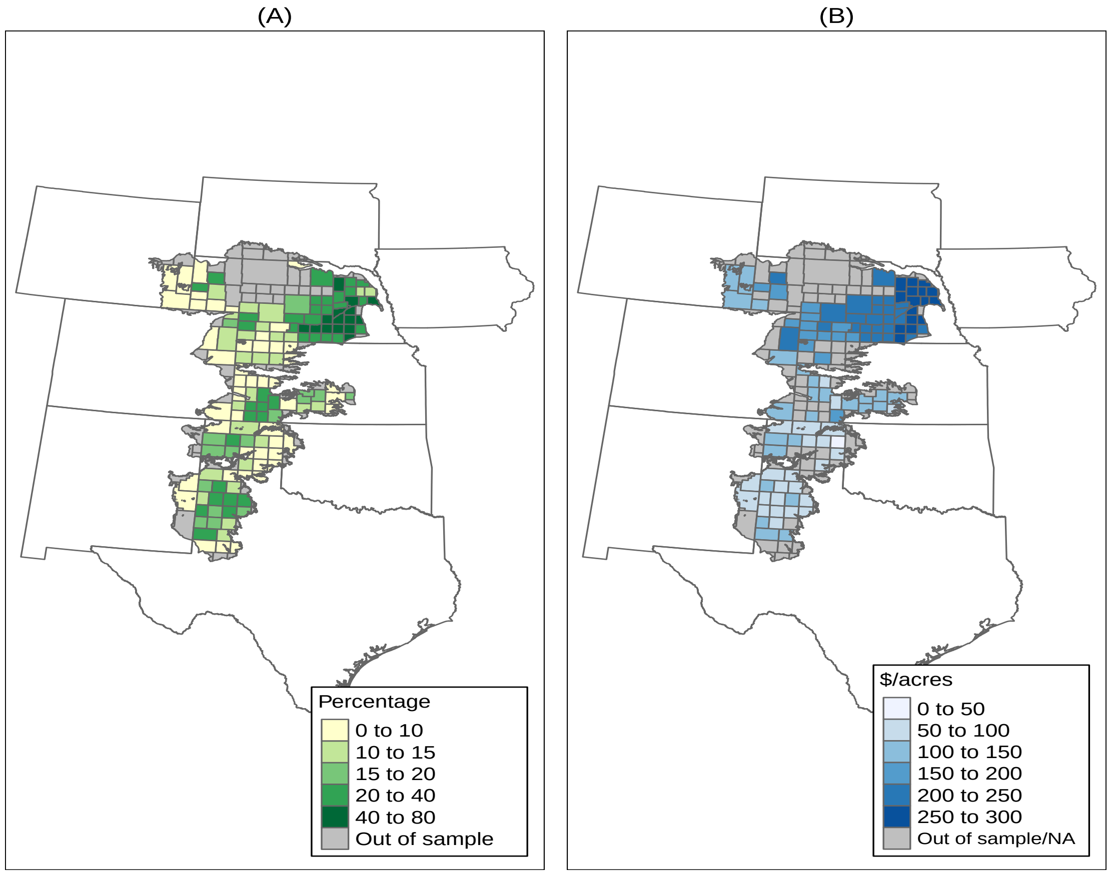

Figure 1.3: (A) Percentage of acres irrigated in 2017 (B) Irrigated rental rates in 2017

1.6 Results and discussion

1.6.1 2SLS Regressions Results

Estimates are presented next using the econometric models described in the previous section, which regress each of the outcomes of interest—percentage of acres irrigated or irrigated rental rates—on saturated thickness. These parameter estimates provide the information required to simulate the impact of the projected saturated thickness in the future. Our focal variables throughout the analysis are the saturated thickness linear splines.

The main results of the regression of percentage of acres irrigated are shown in table 1.2. In column 1, OLS estimates show a positive and significant relationship between irrigated acres and saturated thickness. However, this result cannot be interpreted as causal because the estimates are subject to bias due to feedback effects. Since larger irrigated acres reduce saturated thickness through the hydrologic feedback, we expect the coefficients on saturated thickness to be biased downward. The corresponding 2SLS estimates are shown in column 2. The coefficients on the saturated thickness linear splines are significant at the 5% level and larger than the OLS estimates. We also report the Wu-Hausman test statistic, which examines the null hypothesis that the spline saturated thickness variables are exogenous. The test statistic (11.10) is significant at the 1% level indicating that the downward bias of OLS from the feedback effect is statistically significant. Furthermore, the value of F-statistics testing the null hypothesis that the instruments are equal to zero in the first stage regressions are greater than 10 (65.70 and 106.61). Therefore, weak instruments are not a concern (Staiger and Stock, 1997).

The coefficient on the first saturated thickness linear spline indicates that when the level of saturated thickness is less than 70 ft, a 1 ft decrease in saturated thickness results in a 0.211 percentage point decrease in the area of the county that is irrigated (column 2 of table 1.2). This reflects approximately 2.1% decrease in irrigated acres since 10.24% of a county is irrigated on average when saturated thickness is less than 70 ft. By contrast, when the level of saturated thickness is greater than 70 ft, a 1 ft decrease in saturated thickness results in a 0.044 percentage point decrease in the area of the county that is irrigated. This result reflects about 0.22% decrease in irrigated acres since 21.04% of a county is irrigated on average if saturated thickness is greater than 70 ft. As expected, the effect of a decrease in saturated thickness is larger if the initial saturated thickness is already small.

The magnitude of the average effect of a decrease in saturated thickness in terms of irrigated acres is illustrated using two examples: Wichita County in Kansas and Dallam County in Texas. Saturated thickness in Wichita County has declined from 46 ft in 1982 to 26 ft in 2017. Our results indicate that this decrease of 20 ft in saturated thickness decreased acres irrigated from 65,696 to 46,288 (30% reduction). By comparison, saturated thickness in Dallam has declined from 153 ft in 1982 to 77 ft in 2017. In this case, our results show that the decrease of 76 ft in saturated thickness decreased acres irrigated from 186,135 to

153,919 (17% reduction).

Table 1.2: OLS and 2SLS Regression of Percentage of Acres Irrigated

	OLS	2SLS
	(1)	(2)
$[(1-D_{it})ST_{it} + D_{it}K]$	0.133**	0.211**
	(0.057)	(0.098)
$D_{it}(ST_{it} - K)$	0.035***	0.044***
	(0.011)	(0.014)
Growing Season Precipitation	-0.174*	-0.152
	(0.100)	(0.096)
Growing Season Evapotranspiration	-1.192**	-1.220***
	(0.446)	(0.468)
30-yr Avg. Precipitation	-2.566***	-2.372***
	(0.744)	(0.786)
30-yr Avg. Evapotranspiration	2.790***	3.135***
	(0.690)	(0.703)
30-yr Avg. Growing Degree Days	5.083***	5.539***
	(0.880)	(0.707)
30-yr Avg. Extreme Degree Days	-0.782***	-0.823***
	(0.093)	(0.098)
Hydraulic Conductivity	0.005	0.016
	(0.025)	(0.024)
Specific Yield	63.199	52.986
	(44.801)	(44.954)
Natural Recharge	5.076***	4.912***
	(0.993)	(1.010)
Crop Productivity Index	-13.639	-12.415
	(13.941)	(14.175)
Soil groups	Yes	Yes
State-by-year FE	Yes	Yes
F-statistics for IVs in first stage		65.70
		106.61
Wu-Hausman test		11.10***
N	1112	1112

Standard errors clustered by agricultural district are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Other covariates in the regression of percentage irrigated acres are also significant. The long-term precipitation and evapotranspiration are both significant and show the expected signs. Since precipitation and evapotranspiration are measures of natural water supply and water demand, irrigation is more valuable—and thus irrigated acres are larger—when precipitation is low and evapotranspiration is large. More drought-prone conditions due to climate change would increase the percentage of irrigated acres which would increase the use of groundwater for irrigation. Natural recharge is associated with increases in the percentage of acres irrigated. If a county has greater recharge, then farmers might expect less future depletion which could lead them to invest in irrigation infrastructure, increasing irrigated acres. The crop productivity index is insignificant. However, we also capture the variation in climatic factors and soil productivity affecting crop productivity by including the climatic variables and soil groups.

The main results of the regression of irrigated cash rents are summarized in Table 1.3. We expect that if groundwater is constrained, farmers either switch to less profitable crops or may irrigate less per acre, and this could affect crop yields and net returns on land remaining in irrigation. The feedback between irrigated rents and saturated thickness is less obvious than when considering irrigated acres but is still a concern. Intuitively, it could be that frmers operating in more productive land with higher rental rate have higher incentives to develop irrigation, but the use of more water on this land decreases current saturated thickness. The OLS estimated coefficients on the saturated thickness linear splines are lower than the corresponding 2SLS coefficients, and the Wu-Hausman test statistic (3.64) is significant at the 5% level indicating that the bias of OLS is statistically significant. Table 1.3 also presents the values of the F-statistics (33.03 and 60.08) for the first stage model, which provides support regarding the strength of our instruments.

The 2SLS coefficients on the saturated thickness linear splines show the expected sign, but only the coefficient for the first segment is significant at the 5% level (column 2 of table 1.3). Therefore, when the level of saturated thickness is less than 70 ft, a 1 ft decrease in saturated thickness results in a \$0.72/acre decrease in irrigated cash rent. This effect represents 0.71% of the average irrigated cash rental rate (\$102/acre) in a county with saturated thickness less than 70 ft. By contrast, saturated thickness does not significantly impact irrigated cash rents for levels greater than 70 ft. We also use Wichita and Dallam counties as examples to illustrate the impact of saturated thickness on irrigated rents. Results indicate that a decrease of 20 ft in saturated thickness since 1982 in Wichita County decreased irrigated rental rates from \$102/acre to \$87/acre (14% reduction). By contrast, results show that a decrease of 76 ft in saturated thickness in Dallam County decreased irrigated rental rates from \$101/acre to \$100.2/acre, but this impact is not statistically different from zero.

Table 1.3: OLS and 2SLS Regression of Irrigated Rental Rates

	OLS	2SLS
	(1)	(2)
$[(1-D_{it})ST_{it}+D_{it}K]$	0.510**	0.723**
	(0.228)	(0.294)
$D_{it}(ST_{it}-K)$	0.002	0.010
	(0.030)	(0.029)
Growing Season Precipitation	0.773*	0.815**
	(0.389)	(0.357)
Growing Season Evapotranspiration	0.758	0.784
	(1.491)	(1.336)
30-yr Avg. Precipitation	-6.497**	-6.210***
	(2.476)	(2.321)
30-yr Avg. Evapotranspiration	-10.525***	-9.777***
	(3.524)	(3.409)
30-yr Avg. Growing Degree Days	4.299	5.551
	(3.844)	(3.912)
30-yr Avg. Extreme Degree Days	-0.474	-0.585
	(0.491)	(0.467)
Hydraulic Conductivity	-0.003	0.019
	(0.038)	(0.038)
Specific Yield	-28.002	-46.783
	(148.839)	(149.472)
Natural Recharge	3.550**	3.309**
	(1.448)	(1.338)
Crop Productivity Index	129.681**	130.946***
	(48.428)	(46.301)
Soil groups	Yes	Yes
State-by-year FE	Yes	Yes
F-statistics for IVs in first stage		33.03
		69.08
Wu-Hausman test (p-value)		3.64**
N	819	819

Standard errors clustered by agricultural district are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Our results also highlight the role of other covariates in determining irrigated cash rents and the coefficient estimates generally follow intuition. We find that growing season precipitation positively affects irrigated rents—when growing season precipitation is larger, then a farmer may pump less water so irrigation costs decrease and rent increases. Results also show that a larger crop productivity index is associated with increases in irrigated rents. This result also aligns with intuition given that more productive land for high-value crops may result in higher yield and higher rents.

We use the parameters estimates to estimate the average economic impact of a 1 ft decrease in saturated thickness on returns to land along the extensive and intensive margins (Table 1.4). To estimate uncertainty due to regression estimation, we use the wild cluster bootstrap (WCB) with 1,000 replications which preserves the regressors but resamples the residuals which are used to define new values of the dependent variable following Cameron et al. (2008) and Roodman et al. (2019).

For ease of interpretation, we discuss the average economic impact of a 10 ft decrease in saturated thickness. Our results indicate that a 10 ft decrease in saturated thickness decreased the average returns to land by \$2.27/acre of land overlying the aquifer with initial saturated thickness less than 70 ft. This effect represents a 7.9% decrease in the average returns per acre of cropland[5]. Additionally, 63% of the economic impact corresponds to adjustment through reduced irrigated acreage (extensive margin) (\$1.43/acre) while 37% occurs through reduced irrigated rental rates (intensive margin) (\$0.84/acre).

By contrast, when saturated thickness is greater than 70 ft, a 10 ft decrease in saturated thickness decreased the average returns to land by \$0.46/acre of land overlying the aquifer. This effect represents a 0.9% decrease in the average returns per acre of cropland. Most of the economic impact occurs at the extensive margin (\$0.43/acre) while adjustments at the intensive margin do not have a statistically significant impact on returns to land.

[5]We estimate the change in returns to land per acre of cropland overlying the aquifer as $\frac{\partial \hat{B}_{it}}{\partial ST_{it}} \times \frac{A^{tot.aq}}{A^{cropl.aq}}$, where $A^{tot.aq}$ is total area of the county overlying the aquifer, and $A^{cropl.aq}$ is total cropland area overlying the aquifer. Alternatively, this calculation can be interpreted as the marginal effect per acre of total land divided by the total land that is cropland. To put this marginal effect in relative terms, we divide by the weighted average cropland rental rate (area of cropland irrigated times irrigated rent plus the area of cropland nonirrigated times nonirrigated rent).

Table 1.4: Marginal Economic Impact of a Decrease in Saturated Thickness

Margin of Adjustment	Marginal Effect
Saturated thickness less than 70 ft	
Extensive	-0.143***
	(0.052)
Intensive	-0.084**
	(0.034)
Total	-0.227***
	(0.051)
Saturated thickness greater to 70 ft	
Extensive	-0.043***
	(0.012)
Intensive	-0.002
	(0.007)
Total	-0.046***
	(0.015)

Bootstrap standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.6.2 Projections of Future Economic Returns

The economic impact of projected decreases in saturated thickness across the HPA is estimated next . Parameter estimates are used to simulate how projected changes in saturated thickness impact irrigated acres and irrigated rental rates for each county in our sample, while holding other variables constant. We use the projected values of saturated thickness in 2050 and 2100 from Steward and Allen (2016) to calculate a change from current values in 2020.

As figures 1.4 and 1.5 show, saturated thickness is projected to decrease more rapidly in the central and southern portions of the HPA. The simulation results show that, on average, the two future saturated thickness scenarios result in more severe reductions in annual returns to land in the Central and Southern portions of the HPA. Saturated thickness is projected to decrease on average by 21 ft, 21 ft and 20 ft in Texas, Kansas and Colorado respectively, from 2020 to 2050. Simulation results show that the annual present value of returns to land decrease on average by $53.5, $34.1 and $15.7 million in Texas, Kansas and Colorado, respectively. These effects represent about 11.6%, 5.3% and 7.7% of the current predicted returns to cropland. In addition, irrigated acres are expected to decrease by 20.5%, 13.5% and 23.2% by 2050. By contrast, saturated thickness is projected to decrease on average only by 5 ft in Nebraska which implies an average reduction in the annual present value of returns to land of $10.9 million which represents about 0.42% of the current predicted returns to land. This decrease in saturated thickness would reduce irrigated acres by 1% in 2050.

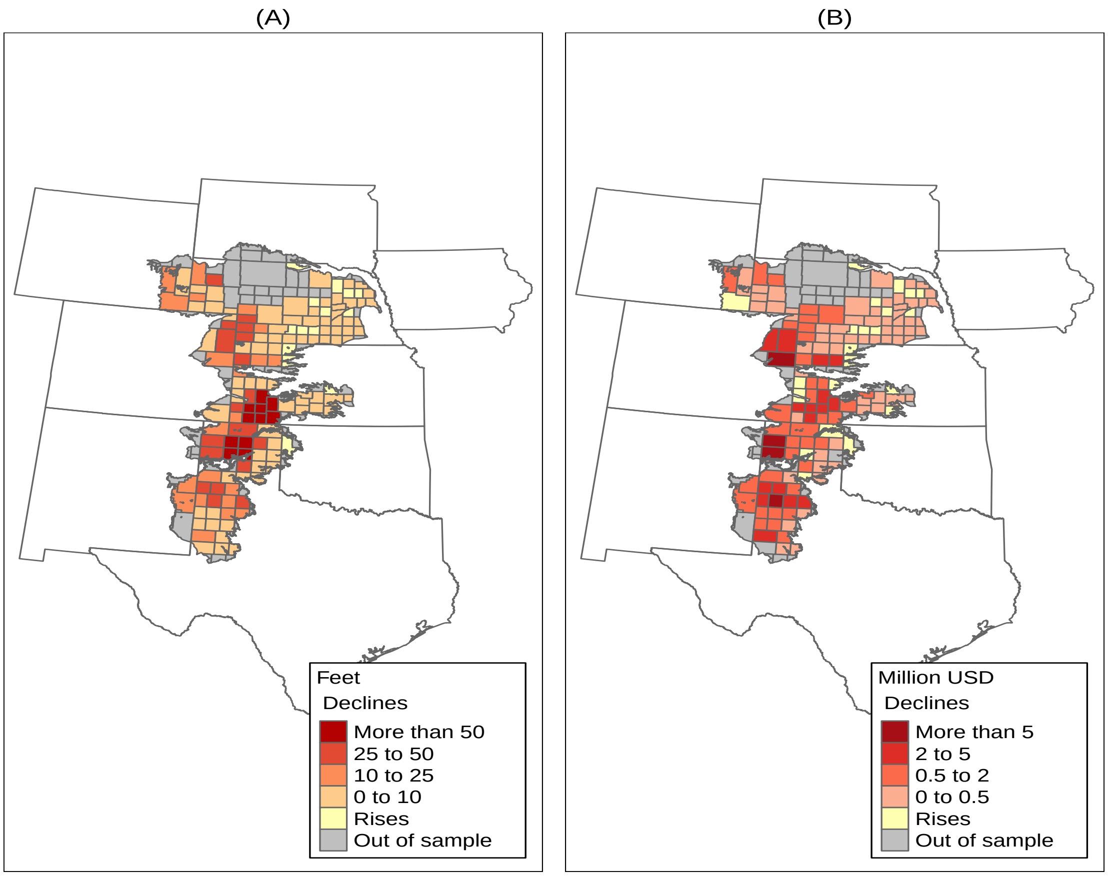

Figure 1.4: (A) Change in saturated thickness 2020 to 2050 (B) Annual change in returns to land

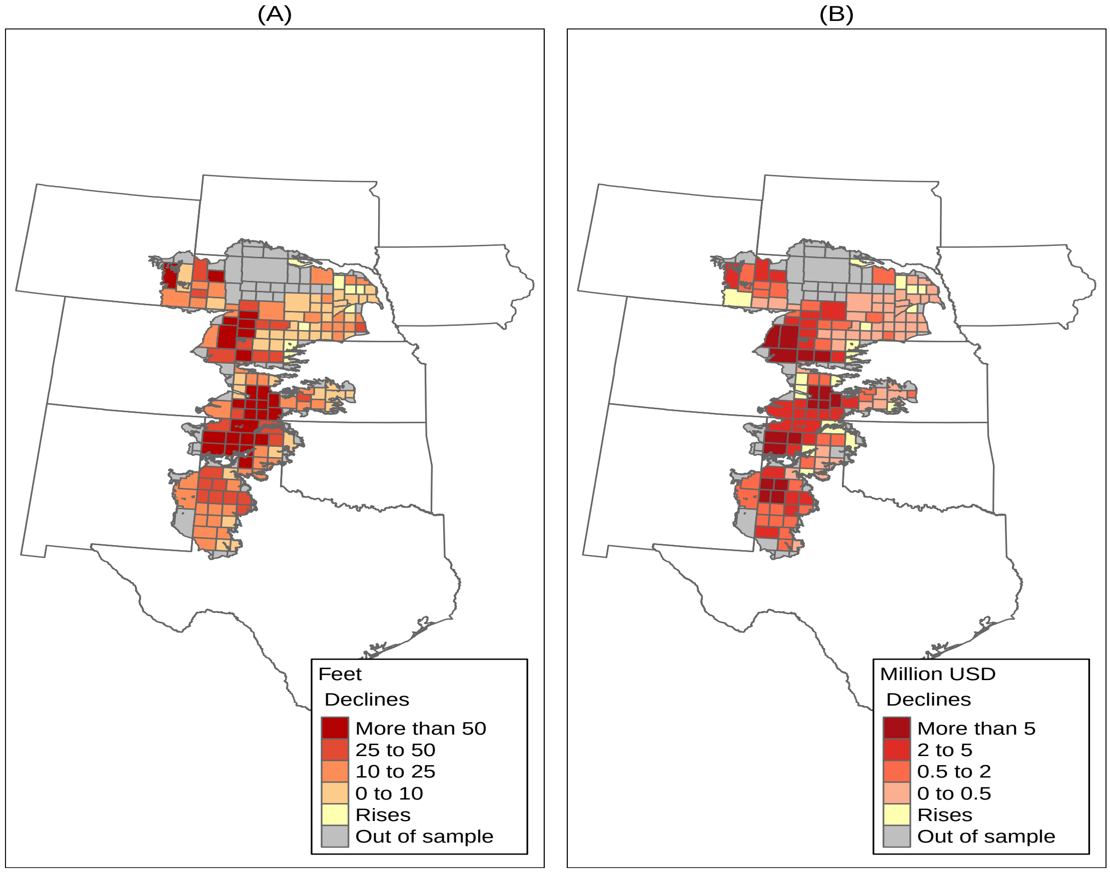

Figure 1.5: (A) Change in saturated thickness 2020 to 2100 (B) Annual change in returns to land

During the longer time period from 2020 to 2100, saturated thickness is projected to decrease on average by 38 ft, 40 ft and 47 ft in Texas, Kansas and Colorado, respectively. In this case, the average annual present value of returns to land are expected to decrease on average by \$84.3, \$86.3 and \$35.0 million in Texas, Kansas and Colorado. These effects represent about 18.3%, 13.4% and 17.2% of the current predicted returns to cropland. In this case, irrigated acres are expected to decrease by 35.8%, 32.7% and 47.3% by 2100. In Nebraska, saturated thickness is projected to decrease on average only by 15 ft in Nebraska which implies an average reduction in the average annual present value of returns to land of \$32.2 million which represents about 1.3% of the current predicted returns to land. Irrigated acres are expected to decrease by 3%.

Across the entire High Plains Aquifer region, the average annual present value of returns to land are projected to decrease by $120.6 million as a result of a projected average decrease in saturated thickness of 14 ft from 2020 to 2050. This effect represents about 3.0% of the current predicted returns to cropland and irrigated acres are expected to decrease by 8.4% by 2050. Similarly, saturated thickness is projected to decrease on average by 29 ft from 2020 to 2100 in the HPA which decreases average annual present value of returns to land by $250.5 million, representing about 6.3% of the current predicted returns to cropland. Irrigated acres are expected to decrease by 17.0% by 2100.

Finally, figure 1.6 shows the trend of projected annual change in returns to land by state for the period 2030-2100 compared to returns in 2020. Kansas and Texas show the strongest downward trend in returns to land. Even though the changes in returns to land are smaller in magnitude in Colorado and Nebraska, these states also show a decreasing trend. Note that these findings extrapolate existing economic conditions and policies into the future in order to isolate the impact of projected declines in groundwater resources alone.

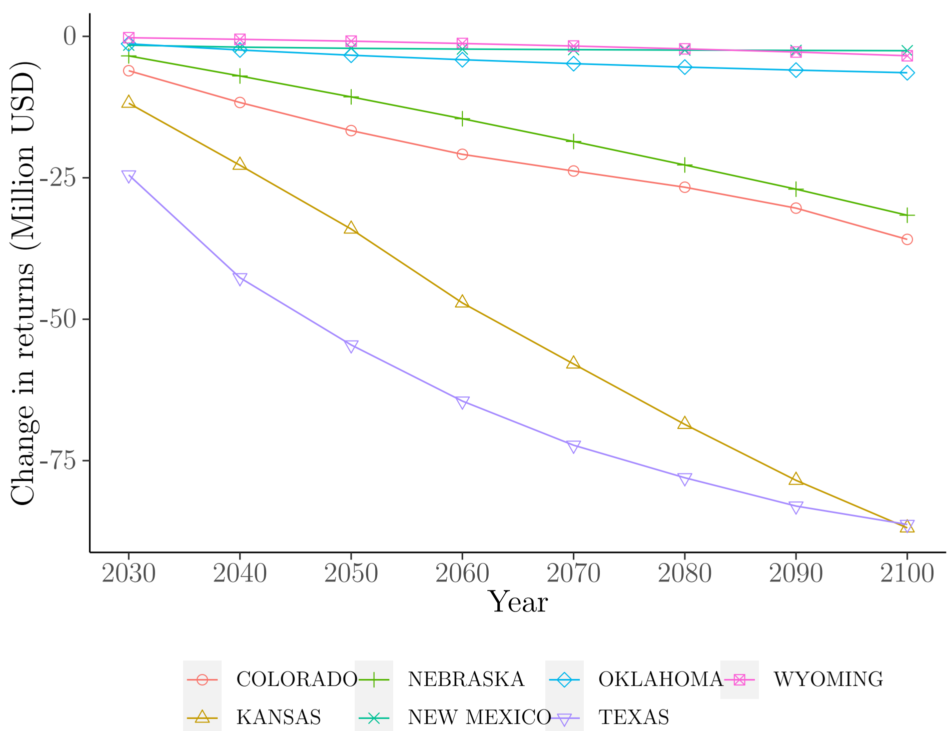

Figure 1.6: Annual change in returns to land compared to 2020

1.6.3 Falsification Test

The purpose of the falsification test is to evaluate the validity of the exclusion restriction. We estimate a reduced form regression using an alternative outcome that should not be affected by pre-development saturated thickness but would be affected by potential confounders. We select nonirrigated cash rental rates as an alternative outcome. The nonirrigated cash rental rates likely reflect the productive ability of the climate and soils and it would violate the exclusion restriction if unobserved productivity is correlated with predevelopment saturated thickness. The results in table 1.5 support the exclusion restriction since pre-development saturated thickness has a statistically insignificant relationship with nonirrigated rents.

Table 1.5: OLS Regression of Nonirrigated Rental Rates

	OLS
$[(1 - D'_{it})ST1930_{it} + D'_{it}K']$	0.152
	(0.151)
$D'_{it}(ST1930_{it} - K')$	-0.018
	(0.035)
Growing Season Precipitation	0.404
	(0.276)
Growing Season Evapotranspiration	-0.818
	(2.331)
30-yr Avg. Precipitation	-1.254
	(2.246)
30-yr Avg. Evapotranspiration	-9.886**
	(4.341)
30-yr Avg. Growing Degree Days	3.297
	(4.124)
30-yr Avg. Extreme Degree Days	-0.298
	(0.516)
Hydraulic Conductivity	0.096*
	(0.049)
Specific Yield	-335.762**
	(130.868)
Natural Recharge	5.377**
	(2.535)
Crop Productivity Index	171.924***
	(52.942)
Soil groups	Yes
State-by-year FE	Yes
R^2	0.87
N	935

Standard errors clustered by agricultural district are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.6.4 Robustness Checks

In this section, we examine whether estimates from our main model specification are sensitive to the inclusion of different fixed effects and to alternative splines' knot locations.

First difference estimator

In Table 1.6 we report coefficient estimates from regressions that include county fixed effects.

The coefficients on saturated thickness are larger than the same coefficients in our main specification. In particular, the effect of saturated thickness on the irrigated rental rates is implausibly large. The use of county fixed effects do not resolve the endogeneity from feedback effects since, for example, a change in irrigated acres affects the change in the stock of groundwater. The effect of saturated thickness on the outcomes of interest becomes even larger when we account for the feedback bias using 2SLS.

Table 1.6: First Difference Regression Results

	Percentage of Irrigated Acres	Irrigated Rental Rates
	OLS	OLS
$[(1-D_{it})ST_{it} + D_{it}K]$	0.376***	9.182***
	(0.090)	(1.753)
$D_{it}(ST_{it} - K)$	0.168***	3.493***
	(0.022)	(0.642)
Growing Season Precipitation	0.072**	-0.125
	(0.032)	(0.320)
Growing Season Evapotranspiration	0.318**	0.322
	(0.152)	(0.714)
Year FE	Yes	Yes
R^2	0.228	0.313
N	987	515

Standard errors clustered by agricultural district are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

GMDs-by-year fixed effects and alternative splines' knot locations

Policies regarding groundwater use not only vary by state but also within states. Local governance institutions that collectively manage the aquifer have been developed as a potential solution to promote water conservation. Colorado, Kansas, Nebraska and Texas use some type of local management district to regulate groundwater use. In Colorado, there are eight Designated Groundwater Basins with 13 groundwater management districts within these basins. Kansas has 5 Groundwater Management Districts with the authority to implement corrective measures for water conservation for a particular region. Nebraska has 23 Natural Resources Districts governed by a publicly-elected board of directors. There are 16 groundwater management areas in Texas and all groundwater conservation districts are part of at least one groundwater management area. In general, groundwater management districts (GMDs) are local districts with additional administrative authority to act on the behalf of local water users. However, the design and implementation of corrective measures for water conservation are heterogeneous across groundwater management districts (Schoengold and Brozovic, 2018).

In our preferred specification, we control for state-by-year fixed effects. However, differences between how each groundwater management district choose to design policy might affect the outcomes of interest. Table 1.7, Panel A, reports the results of regressions that include groundwater management districts (GMDs) by year fixed effects. The pattern of the results is unchanged, perhaps because many policy changes were only implemented in the HPA recently (see Schoengold and Brozovic (2018) for a detailed discussion). For instance, Kansas established the first Local Enhanced Management Area (LEMA), Sheridan 6, in 2013 which covers a local township sized portion of the GMD to reduce water allocations. Other groundwater management plans in Kansas have not substantially reduced water use during our sample period (Perez-Quesada and Hendricks, 2021).

Table 1.7, Panels B and C, report the results of regressions for different locations of the spline knots. We increase (decrease) by 10 ft both the saturated thickness spline knot (K) and the predevelopment saturated thickness spline knot (K'). The similarity of the estimates of the percentage of irrigated acres and irrigated rental rates regressions to those obtained with the previous knots suggests that our results are robust to changes in the optimal knot. The coefficient of the saturated thickness linear spline is larger (smaller) than before when the new threshold is smaller (larger), which may impose a larger (smaller) restriction on well yield.

Table 1.7: Regression Results based on GMDs-by-year Fixed Effects and Alternative Spline Knot

	Percentage of Irrigated Acres	Irrigated Rental Rates
	2SLS	2SLS
Panel A: Results with GMDs-by-year FE		
$[(1-D_{it})ST_{it}+D_{it}K]$	0.211***	0.610***
	(0.073)	(0.150)
$D_{it}(ST_{it}-K)$	0.044***	-0.031
	(0.015)	(0.026)
GMDs-by-year FE	Yes	Yes
F-statistic for IVs in first stage	43.38	46.39
	73.13	49.19
Wu-Hausman test	20.31***	1.83
Panel B: Results with $K=60$ and $K^{'}=80$		
$[(1-D_{it})ST_{it}+D_{it}K]$	0.241*	1.064**
	(0.124)	(0.448)
$D_{it}(ST_{it}-K)$	0.046***	0.011
	(0.015)	(0.030)
GMDs-by-year FE	Yes	Yes
F-statistic for IVs in first stage	46.90	36.84
	97.88	62.36
Wu-Hausman test	11.32***	5.69**
Panel C: Results with $K=80$ and $K^{'}=100$		
$[(1-D_{it})ST_{it}+D_{it}K]$	0.191**	0.543**
	(0.086)	(0.225)
$D_{it}(ST_{it}-K)$	0.041***	0.008
	(0.014)	(0.030)
GMDs-by-year FE	Yes	Yes
F-statistic for IVs in first stage	59.96	24.31
	108.22	72.07
Wu-Hausman test	10.91***	2.30

Standard errors clustered by agricultural district are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.7 Conclusions

In this paper, we estimate how changes in groundwater stocks affect the returns to agricultural land in the High Plains Aquifer of the central US. We address feedback effects by exploiting hydrologic variation in pre-development saturated thickness formed during natural processes in a previous geological era. Ignoring the feedback effect results in significant downward bias.

We find that 63% of the economic impact of a decrease in the stock of groundwater corresponds to adjustment through reduced irrigated acreage (extensive margin), and 37% occurs through reduced irrigated rental rates (intensive margin) when saturated thickness is less than 70 feet, and nearly all of the response is at the extensive margin when saturated thickness is larger. The simulation results show that the economic impact of the projected decrease in saturated thickness varies significantly across regions of the HPA. The most substantial decrease in returns to land are expected to occur in the Central and Southern portions of the aquifer. There, the annual present value of returns to land are expected to decrease on average by \$53.5, \$34.1 and \$15.7 million by 2050 and by \$84.3, \$86.3 and \$35.0 million by 2100 in Texas, Kansas and Colorado, respectively. Furthermore, the average annual present value of returns to land are expected to decrease in the High Plains region by \$120.6 million by 2050 and by \$250.5 million by 2100.

The results of this study provide useful information for the management of groundwater. We estimate the economic impact of varying groundwater stocks and, as a result, we are able to predict the impact of a projected change due to aquifer depletion. These results inform groundwater managers about the projected magnitude of reductions in returns under the existing policy framework and potential gain from implementing policies that could preserve the stock of groundwater.

Chapter 2

Corn Production and Groundwater Scarcity in the US High Plains

2.1 Introduction

Groundwater irrigation has enhanced both the productivity and profitability of the agricultural sector in many arid regions worldwide. Irrigated agriculture contributes 40% of total global food production (Mrad et al., 2020) but it is depleting groundwater resources in many regions, including the Central Valley of California and the High Plains of the United States, South America, the North China Plain and in many parts of India (Famiglietti, 2014; Richey et al., 2015). One estimate is that these water limitations could require the transition of 20-60 Mha of cropland from irrigated to nonirrigated management by 2100 (Elliott et al., 2014).

The High Plains Aquifer (HPA) in the United States is a major source of water for irrigated crop production and contributes significantly to related sectors (Edwards and Smith, 2018). In 2015, groundwater withdrawals from the HPA represented about 47% of the total water used for irrigation in the US (Dieter et al., 2018). However, groundwater resources are significantly depleted in some areas of the HPA which can make continued irrigation inviable (Mrad et al., 2020; Scanlon et al., 2012). For example, Haacker et al. (2016) consider that irrigated crop production is impractical once saturated thickness is less than 30 ft and predict that 25 to 40% of the aquifer will be under this threshold between 2012 and 2100. Deines et al. (2020) estimate that 24% of currently irrigated lands in the HPA will not support irrigated agriculture by 2100.

Total US corn production represents about 31% of global corn production (USDA, 2022). The High Plains region is responsible for about 25% of the total US corn production, and approximately 46% of the total corn production in the High Plains comes from irrigated agriculture (USDA-NASS). Moreover, corn production contributes significantly to the High Plains livestock, food processing and energy sectors that depend on corn as a key input of their products. In general, the production of corn has increased in the High Plains over time (Figures A.2- A.7, Appendix) due to the improvements in corn yield. However, we should not conclude from this trend that depletion has no impact on production since production of corn could have increased even more in a counterfactual scenario with no aquifer depletion.

Current literature on the potential impact of aquifer depletion on corn production remains limited to the use of model simulations that impose restrictive assumptions on irrigator behavior. Steward et al. (2013) project the impact of declining groundwater levels on corn production but they assume that irrigated corn production is a fixed proportion of pumped groundwater. Cotterman et al. (2018) evaluate the combined effects of climate change and aquifer depletion on corn production using a mechanistic crop simulation model. A recent study by Lopez et al. (2022), show the impact on US corn production of limiting groundwater use to available recharge assuming that the only strategy for decreasing water use is by reducing production through the use of land fallowing. Mrad et al. (2020) estimate peak crop production for the High Plains using a dynamic system that was calibrated using historical time series data on irrigated area, volume of irrigation, and aggregated crop production.

Most relevant to our paper, two recent studies in India use econometric models to estimate the impacts of declining groundwater levels on staple grain production and cropping intensity (Bhattarai et al., 2021; Jain et al., 2021). In particular, Bhattarai et al. (2021) estimate the impact of well depth on cropland and crop yield but they do not account for potential endogeneity of well depth due to bias from feedback effects of irrigated crop production affecting resource conditions.

Our paper estimates how differences in the stock of groundwater across the aquifer affect corn production in the High Plains region using observed data on groundwater stocks and corn production. Bias from feedback effects might arise because as farmers extract more water to irrigate corn, the stock of groundwater decreases. We avoid this bias by exploiting variation in pre-development saturated thickness that is unrelated to irrigation behavior since it was determined by the structure and features of the pre-Ogallala surface roughly 5 to 24 million years ago.

Farmers may adjust corn production in response to saturated thickness in several different ways. Thus, we allow for different margins of adjustment. First, changes in corn production when a field is converted from irrigated to nonirrigated. Second, changes in corn production when farmers reduce the proportion of corn acres on irrigated land by switching to less water intensive crops. Third, changes in corn yield as less water is applied to irrigated fields. We use county-level datasets on acres irrigated and corn yield to examine the impact of changes in the stock of groundwater on (i) irrigated acres and (ii) corn yield, whereas we use field-level crop data derived from satellite imagery to estimate (iii) the change in corn production when a field is irrigated rather than nonirrigated, and the impact of changes in the stock of groundwater on (iv) the probability of planting corn. These data are combined with hydrologic characteristics of the aquifer, irrigation status of each field, and climatic and soil characteristics.

We find that the annual production of corn would decrease by 20.1, 19.3, 7.5 and 1.2 million bushels in Kansas, Nebraska, Colorado and Wyoming due to a uniform 10 ft decrease in saturated thickness. These decreases in annual corn production represent 6.6%, 1.6%, 7.3% and 17.7% of the 2010-2019 average corn production across counties overlying the aquifer in each state. Similarly, the annual production of corn is expected to decrease by 1.1 and 14.6 million bushels in Oklahoma and Texas. These reductions in corn production represent 5.3% and 9.2% of the 2010-2019 average corn production across counties overlying the aquifer in each state.

Our paper provides two main contributions. First, our paper is the first to use econometric models to estimate how depleting groundwater stocks will affect corn production. Second, we improve on existing studies in different regions by estimating crop production impact using initial groundwater conditions as an instrument to reduce bias from feedback effects. Although our empirical analysis focuses on the High Plains in the US, our empirical strategy could be used to estimate how changes in the stock of groundwater affect corn production in other regions.

2.2 Decomposition of the Impact of Groundwater Availability on Corn Production

Reductions in groundwater availability impact production of corn through two main mechanisms: decreasing well yields and increasing pumping costs. Reductions in well yields occur because reduced saturated thickness is no longer sufficient to support high pumping rates. The cost of pumping increases with reduced saturated thickness since more energy is required to pump groundwater from greater depths. We do not separately estimate these two different mechanisms, but instead we use reduced form models to estimate the overall impact of a change in saturated thickness.

Farmers may adjust corn production in response to saturated thickness in several different ways. To understand these different margins of adjustment, the production of corn per acre of cropland (F_{ct}) in county c and year t is modeled as a function of saturated thickness using the following equation:

$$F_{ct}(ST_{ct}) = \varphi_{ct}(ST_{ct})\psi_{ct}^{irr}(ST_{ct})\Upsilon_{ct}^{irr}(ST_{ct}) + (1 - \varphi_{ct}(ST_{ct}))\psi_{ct}^{non}\Upsilon_{ct}^{non},$$

where ST_{ct} is saturated thickness which reflects groundwater stock, φ_{ct} is the proportion of cropland area that is irrigated, ψ_{ct}^{irr} (ψ_{ct}^{non}) is the share of irrigated (nonirrigated) cropland planted to corn, and Υ_{ct}^{irr} (Υ_{ct}^{non}) is the yield of irrigated (nonirrigated) corn. Therefore, the first first term represents corn production on irrigated cropland and the second term is corn production on nonirrigated cropland. Total production of corn in the county is obtained by multiplying the equation times the total acres of cropland in the county. Equation 2.1 shows how farmers adjust their corn production decisions as a response to an exogenous change in groundwater availability:

$$
\begin{aligned}
\frac{\partial F_{ct}(ST_{ct})}{\partial ST_{ct}} &= \overbrace{\underbrace{\frac{\partial \varphi_{ct}(ST_{ct})}{\partial ST_{ct}}}_{\textbf{(a.1)}} \underbrace{\left[\psi_{ct}^{irr}(ST_{ct})\Upsilon_{ct}^{irr}(ST_{ct}) - \psi_{ct}^{non}\Upsilon_{ct}^{non}\right]}_{\textbf{(a.2)}}}^{A} + \\
&\overbrace{\underbrace{\frac{\partial \psi_{ct}^{irr}(ST_{ct})}{\partial ST_{ct}}}_{\textbf{(b)}} \varphi_{ct}(ST_{ct})\Upsilon_{ct}^{irr}(ST_{ct})}^{B} + \overbrace{\underbrace{\frac{\partial \Upsilon_{ct}^{irr}(ST_{ct})}{ST_{ct}}}_{\textbf{(c)}} \varphi_{ct}(ST_{ct})\psi_{ct}^{irr}(ST_{ct})}^{C}.
\end{aligned}
\tag{2.1}
$$

Farmers are assumed to maximize their utility subject to the constraint that well yield imposes on instantaneous application rates (Foster et al., 2014). When saturated thickness is above a certain level, well yield is not a binding constraint and different levels of saturated thickness may have minimal impact on producer behavior. But for lower saturated thickness where well yields become constraining, farmers adjust their behavior through the extensive or intensive margins. Component A (i.e., extensive margin) reflects how corn production changes when a field is converted from irrigated to nonirrigated due to a change in saturated thickness. Component a.1 is the change in irrigated cropland area and this is multiplied by the difference in corn production on an acre of irrigated versus nonirrigated cropland (component a.2). Component B (i.e., the crop switching margin) captures how corn production changes when farmers reduce the proportion of corn acres on irrigated land by switching to less water intensive crops. Component C (i.e., the corn yield margin) accounts for changes in corn yield as less water is applied to irrigated fields.

2.3 Empirical Strategy and Data

To examine the impact of a change in saturated thickness on corn production, we separately estimate each subcomponent ($a.1$), ($a.2$), (b) and (c) of equation 2.1 using different model specifications and several sources of data. Even after controlling for relevant confounders, our estimates of subcomponent ($a.1$), (b) and (c) are subject to potential bias from feedback effects between saturated thickness and irrigation behavior. Therefore, we use the empirical strategy implemented in chapter 1 where pre-development saturated thickness—the saturated thickness that existed before any effects imposed by human activity—is used as an instrument to obtain a source of plausibly exogenous variation in saturated thickness. We consider a nonlinear relationship between saturated thickness and corn production since previous studies show that declines in well yield may have negative nonlinear impacts on irrigated area (Foster et al., 2015, 2014).

The study area includes 141 counties in six states overlying the HPA—Colorado, Kansas, Nebraska, Oklahoma, Texas and Wyoming. We restrict the sample to counties with a proportion of their total area over the aquifer greater than 60% to ensure the availability of groundwater for irrigation. The area of the sand hills in Nebraska overlying the aquifer has minimal irrigation because the sandy soil makes the region unsuitable for crop farming (Peterson et al., 2016; USDA-NRCS, 2006). Therefore, counties with greater than 55% of their area in the sand hills are excluded from the analysis. Next, we describe each model and sources of data.

2.3.1 Impact of Saturated Thickness on Irrigated Acres (a.1)

Econometric Model

To estimate the impact of saturated thickness on irrigated acres, we use the econometric model described below in equation 2.2. Our estimates are subject to downward bias due to the feedback effect between saturated thickness and irrigated acres. This occurs since extraction of groundwater increases and saturated thickness decreases as farmers expand irrigated acres. Therefore, a two-stage least square (2SLS) model is estimated for irrigated acres using pre-development saturated thickness as an instrument. The nonlinear relationship between saturated thickness on irrigated acres is represented using linear spline regression, which is a piecewise linear function that fits a line in each segment of the saturated thickness space defined by the knots while requiring continuity at the knot (Harrell, 2001).

The second-stage equation is:

$$\begin{aligned}\varphi_{ct}^{irr} = \beta_0 + \beta_1[(1 - D_{ct})ST_{ct} + D_{ct}K] + \beta_2 D_{ct}(ST_{ct} - K) + \\ \alpha' X_{ct} + \tau' Z_c + \delta_g + \gamma_{rt} + \varepsilon_{ct},\end{aligned} \tag{2.2}$$

where K is the location of the spline knot, and

$$D_{ct} = \begin{cases} 0 & \text{if } ST_{ct} < K \\ 1 & \text{if } ST_{ct} \geq K. \end{cases}$$

The variable φ_{ct}^{irr} denotes the percentage of acres irrigated of the cropland over the aquifer in county c at time t, ST_{ct} is the average saturated thickness in the county, and $[(1-D_{ct})ST_{ct} + D_{ct}K]$ and $D_{ct}(ST_{ct} - K)$ are linear spline functions of saturated thickness. The vector X_{ct} contatins two time-variant explanatory variables. We include the contemporaneous cumulative measures for precipitation and reference evapotranspiration demand within the growing season (April 1 - September 30) to isolate contemporaneous weather effects. The vector Z_c includes several time-invariant variables described next.

We include four long-run climate variables to describe the climate in each county: average precipitation, average reference evapotranspiration, the average number of growing degree days between 10°C and 30°C, and the average number of degree days greater than 32°C. To account for the aquifer's characteristics in each county, we include three variables: hydraulic conductivity, specific yield and natural recharge. Hydraulic conductivity is a measure of the rate at which water can move laterally to a well, and specific yield is the volume of water per unit volume of aquifer that can be extracted. Where hydraulic conductivity and specific yield have higher values, we expect an increase in the well yield as water moves more readily to a well. Natural recharge is the seepage of water into an aquifer, not including return flows from irrigation. It controls for changes in agricultural outcomes as a consequence of different expected rates of aquifer depletion that affect expectations of future aquifer stocks. Finally, we include a national commodity crop productivity index for corn and soybeans to account for the soil's suitability for corn and soybeans.

The fraction of county area in each soil group is represented by δ_g; γ_{rt} are state-by-year fixed effects for state r and year t which absorb the effects of any arbitrary shock, including technological change, variation in commodity price and groundwater laws, which is specific to a state in any given year; and ε_{ct} are idiosyncratic errors. Based on exploratory analysis of our data and previous studies described above, we allow for one spline knot location ($K = 70$).

The first stage regressions are defined as:

$$[(1 - D_{ct})ST_{ct} + D_{ct}K] = \theta_0^1 + \theta_1^1[(1 - D_c^{'})ST1930_c + D_c^{'}K^{'}] + \theta_2^1 D_c^{'}(ST1930_c - K^{'}) + \\ + \phi_1^1 X_{ct} + \phi_2^1 Z_c + \delta_g^1 + \gamma_{rt}^1 + v_{ct}^1,$$

and

$$(ST_{ct} - K) = \theta_0^2 + \theta_1^2[(1 - D_c^{'})ST1930_c + D_c^{'}K^{'}] + \theta_2^2 D_c^{'}(ST1930_c - K^{'}) + \\ + \phi_1^2 X_{ct} + \phi_2^2 Z_c + \delta_g^2 + \gamma_{rt}^2 + v_{ct}^2,$$

where $K^{'}$ is the spline knot and

$$D_c^{'} = \begin{cases} 0 & \text{if } ST1930_c < K^{'} \\ 1 & \text{if } ST1930_c \geq K^{'}. \end{cases}$$

It is important to note that there are two endogenous explanatory variables ($[(1-D_{ct})ST_{ct}+D_{ct}K]$ and $(ST_{ct}-K)$), and our two instruments are $[(1-D_c^{'})ST1930_c+D_c^{'}K^{'}]$ and $D_c^{'}(ST1930_c-K^{'})$. The variable $ST1930_c$ is pre-development saturated thickness (i.e., the saturated thickness in 1930) and the instruments, $[(1-D_c^{'})ST1930_c+D_c^{'}K^{'}]$ and $D_c^{'}(ST1930_c-K^{'})$, are linear spline functions of pre-development saturated thickness with $K^{'}=90$. Since pre-development saturated thickness is larger than current saturated thickness, the selected knot for the instrument is also larger.

For the statistical inference, the standard errors are clustered at the agricultural district level to adjust for heteroskedasticity, within-county correlation over time and spatial correlation between counties within a district. We follow Bester et al. (2011), who propose clustering by spatial groups as a simple and flexible method to account for spatial correlation. Bester et al. (2011) show that clustering results in valid inference if cluster-level averages are approximately independent.

IV Assumptions

To identify β_1 and β_2 in equation 2.2, the instruments must account for the saturated thickness variation. As shown in chapter 1, it is apparent that the geographic patterns of saturated thickness in 2017 resembles the pattern of pre-development saturated thickness in 1930. In general, the greatest contemporaneous saturated thickness occurs in those areas where initial saturated thickness was also the largest.

Identification also requires satisfying the exclusion restriction. The exclusion restriction is that conditional on the controls included in the regression, the pre-development saturated thickness has no effect on the percentage of acres irrigated other than its effect through the current saturated thickness. This exclusion restriction is plausible since the pre-development saturated thickness was shaped by the structure and features of the Ogallala geological formations that existed long before human settlement, so it is unrelated to human activity (see chapter 1 for a detailed explanation).

Data

Table 3.2 displays descriptive statistics for the variables in our model. The variables used in the model are obtained from a variety of sources. Irrigated area and total cropland area at the county-level are available every five years from the US Census of Agriculture. Cropland area over the aquifer is calculated as the total cropland area in the county times the share of the county overlying the aquifer. We calculate the percentage of acres irrigated by dividing the irrigated acres by the total cropland area of the county overlying the aquifer. We construct a balanced panel of 141 counties over the HPA from 1982 to 2017, resulting in a total of 1,128 observations.

Table 2.1: Summary statistics for variables in the econometric analysis

Variables	Mean	Std. Dev.
Percentage of Acres Irrigated	30.61	20.33
Predevelopment Saturated Thickness (ft)	172.50	103.54
Saturated Thickness (ft)	149.69	102.50
Growing Season Precipitation (in)	15.85	4.84
Growing Season Evapotranspiration (in)	34.46	2.89
30-yr Avg. Precipitation (in)	16.31	3.10
30-yr Avg. Evapotranspiration (in)	34.56	2.60
30-yr Avg. Growing Degree Days (hundreds)	18.36	2.60
30-yr Avg. Extreme Degree Days	32.33	17.57
Hydraulic Conductivity (ft/day)	81.40	47.14
Specific Yield (prop.)	0.16	0.02
Natural Recharge (in)	2.62	2.13
Crop Productivity Index (prop.)	0.30	0.14

Daily gridded weather data are obtained from PRISM and aggregated to the county level. We calculate the cumulative measure for precipitation and reference evapotranspiration demand within the growing season (April 1 - September 30) for each year. Reference evapotranspiration is a measure of the evaporative demand independent of crop characteristics and soil factors within a county. It is calculated using the reduced-set Penman-Monteith method following Hendricks (2018). We also construct four long-run climate variables: average precipitation, average reference evapotranspiration, the average number of degree days between 10°C and 30°C, and the average number of degree days greater than 32°C. We calculate the cumulative measure for each of these four variables within the growing season (April 1 - September 30) for each year and then calculate a 30-year average (1987-2017).

Hydrologic characteristics of the HPA are obtained from two different sources. Pre-development saturated thickness and the average annual saturated thickness are obtained from Steward and Allen (2016). Hydraulic conductivity, specific yield and natural recharge are obtained from the US Geological Survey. This hydraulic conductivity data set consists of contours and polygons that we aggregate to the county level (USGS, 1998). We use a raster of the average specific yield for the HPA and aggregate it to the county level (McGuire et al., 2012; USGS, 2012). Natural recharge data are also obtained from a raster and aggregated to the county level (Houston et al., 2013; USGS, 2011). The average 2000-09 recharge is estimated by USGS using the Soil-Water Balance (SWB) model which assumes that irrigation systems are 100% efficient and there is no surplus irrigation water for recharge. Thus, natural recharge does not include return flows from irrigation (Stanton et al., 2011).

Major soil groups are obtained from Hornbeck and Keskin (2014). For example, soil groups appearing within the HPA include: alluvial, brown, chernozem, and chestnut[1]. The national commodity crop productivity index for corn and soybeans is obtained from the Soil Survey Geographic database (SSURGO). This variable ranges from 0.01 (low productivity) to 0.99 (high productivity).

2.3.2 Change in Corn Production when Field is Irrigated rather than Nonirrigated (a.2)

Econometric Model

We use linear regression to estimate the following statistical model:

$$\psi_{it}\Upsilon_{it} = \beta_{0r} + \beta_{1r} I_{it} + \tau_r^{'} Z_i + \mu_{scr} + \gamma_{ltr} + \varepsilon_{it}, \tag{2.3}$$

[1]A map can be found in the Hornbeck and Keskin (2014)'s online Appendix: https://assets.aeaweb.org/asset-server/articles-attachments/aej/app/app/0601/2012-0256_app.pdf

where the dependent variable $\psi_{it}\Upsilon_{it}$ is the per acre corn production in field i in year t, which is calculated as whether or not field i is planted to corn (ψ_{it}) times the corn yield (Υ_{it}). We estimate this regression separately for the northern and southern portions of the HPA to account for heterogenous effects across regions. Therefore, each of the parameters have an r subscript to denote that they differ between the northern and southern regions. The northern regions includes Colorado, Kansas, Nebraska and Wyoming, while the southern includes Oklahoma and Texas.

I_{it} is a dummy variable equal to 1 if field i is irrigated. Z_i is a vector which includes precipitation and temperature normals during the growing season to control for long-run climate variation. μ_{scr} are soil-county fixed effects capturing time-invariant soil and county characteristics. γ_{ltr} are state-by-year fixed effects for state l and year t which control for spatial-temporal variation and allow for a separate effect for each possible combination of state and year, and ε_{it} are idiosyncratic errors. The standard errors are clustered at the soil-county level to adjust for heteroskedasticity, within-field correlation over time and spatial correlation between fields within a soil-county group.

Data

Table 2.2 presents summary statistics of the variables used in model estimation. Production of corn per acre used as the dependent variable in equation 2.3, is equal to irrigated corn yield if corn was planted in field i in year t, equal to nonirrigated corn yield if nonirrigated corn was planted and equal to zero if another crop was planted. To identify what crop is grown in each field, we use crop data from the Cropland Data Layer (CDL) developed by the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA)[2]. The CDL provides annual information on what crop is being grown at every 30-by-30 meter pixel in the US from 1997 to 2021. Our analysis uses field crop data from 2008-2017 in 141 counties that overlay the High Plains Aquifer. We use Common Land Unit (CLU) boundaries in 2007 from Farm Service Agency to approximate "field"

[2] The CDL can be downloaded at `https://nassgeodata.gmu.edu/CropScape/`. See Boryan et al. (2011) for details on the CDL methodology.

boundaries[3]. The CLU data were obtained from Woodard (2016). We define a point near to the centroid of the CLU as our unit of analysis[4] (Appendix, Figure A.1).

Data on where and when irrigation occurs is obtained from Annual Irrigation Maps - High Plains Aquifer (AIM-HPA). This dataset was produced from Landsat satellite data in (Deines et al., 2019) and provides moderately high resolution (30 m) irrigation map time series from 1984 to 2017 over the aquifer[5]. We combine the CDL and AIM-HPA datasets to classify a field as irrigated corn, nonirrigated corn, or other. We also use AIM-HPA irrigation classification as our key explanatory variable.

Table 2.2: Summary statistics for variables in the econometric analysis

	North		South	
Variables	Mean	Std. Dev.	Mean	Std. Dev.
Corn Production ($\psi_{it}\Upsilon_{it}$)	71.25	89.90	17.94	55.31
Proportion of Corn within irrigated fields	0.61	0.49	0.24	0.42
Proportion of Corn within nonirrigated fields	0.22	0.42	0.009	0.092
Irrigated Corn Yield (Bu/acre)	192.32	18.44	179.17	31.27
Nonirrigated Corn Yield (Bu/acre)	96.96	44.53	53.25	23.51
Precipitation Normals (in)	18.15	3.15	13.39	1.40
Temperature Normals (degrees)	19.11	1.22	21.87	0.99

Annual data on irrigated and nonirrigated corn yields at the county-level are obtained from the National Agricultural Statistics Service (NASS) for the period 2008-2017. Since the number of reported counties is small for some states during the 2008-2017 period, we use corn yield at the agricultural district level to fill missing values. We link yield and CDL data to assign yield values to each field.

Climate information is summarized by climate normals defined by the National Oceanic and Atmospheric Administration (NOAA) as “three-decade averages of climatological variables including tempreature and precipitation.” Monthly long-term average gridded precipi-

[3]A CLU is the smallest contiguous unit of agricultural land under common land cover, land management, and ownership. See here for more details https://www.fsa.usda.gov/programs-and-services/aerial-photography/imagery-products/common-land-unit-clu/index

[4]Only points corresponding to CLU larger or equal to 15 acres are included in the analysis.

[5]The AIM-HPA can be downloaded at https://www.hydroshare.org/resource/a371fd69d41b4232806d81e17fe4efcb/

tation and temperature data are obtained from PRISM. We use the current PRISM normals which covers the period 1991-2020. We calculate the long-term average precipitation and temperature during the growing season (April 1 - September 30) for each field in the sample.

We collected soil data from Soil Survey Geographic (SSURGO) database from NRCS, which includes data on physical and chemical soil properties[6]. We use map units provided by the SSURGO data to create the soil fixed effects.

2.3.3 Impact of Saturated Thickness on the Probability of Planting Corn (b)

Econometric Model

We expect that if groundwater is constrained, farmers may switch from corn towards less water intensive crops. To estimate the impact of saturated thickness on the share of irrigated corn acres we use the same empirical strategy as we use to estimate subcomponent (a.1) since feedback effects between the share of irrigated corn acres and saturated thickness could bias our estimates. Intuitively, it could be that farmers operating in more productive lands have higher incentives to plant corn and develop irrigation which will impact groundwater stocks. Thus, a 2SLS model is estimated for the share of irrigated corn acres using the same instrument, pre-development saturated thickness, that we use in section 2.3.1.

The second-stage equation is:

$$\psi_{it}^{irr} = \beta_{0r} + \beta_{1r}[(1 - D_i)ST_i + D_iK] + \beta_{2r}D_i(ST_i - K) + \tau_r^{'}Z_i + \alpha_{rc} + \gamma_{rt} + \varepsilon_{it}, \tag{2.4}$$

where the dependent variable ψ_{it}^{irr} is a dummy equal to 1 if corn is planted in year t conditional on field i being irrigated. ST_i is the average saturated thickness in 2015. $[(1-D_i)ST_i+D_iK]$ and $D_i(ST_i - K)$ are linear spline functions of saturated thickness defined in section 2.3.1. The vector Z_i includes climate and soil variables which are time-invariant. Given that farmers

[6] https://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx

decide what crops to plant prior to the start of the growing season, we include precipitation and temperature normals during the growing season to capture their expectation of weather conditions during the next growing season. We include the following five soil characteristics as controls: the national commodity crop productivity index for corn, electrical conductivity, soil organic carbon, the percentage of clay soil and the percentage of silty soil. α_{rc} are county fixed effects to control for any common time-invariant characteristics such as geographic locations, climate and soil quality for each county. γ_{rt} are year fixed effect to control for any common weather shocks, technological progress, and policy changes within each year, and ε_{it} are idiosyncratic errors.

Similarly to the estimation of subcomponent (a.2), we allow each coefficient to vary between the northern and southern regions as denoted by the subscript r. The effect of saturated thickness on the probability of planting corn might differ across the regions with different cropping practices. In particular, cotton is a viable and popular crop alternative in the south, but not the north. The standard errors are clustered at the county level to adjust for heteroskedasticity, within-field correlation over time and spatial correlation between fields within a county.

Data

We use the same data that we use to estimate subcomponent (a.2) described in section 2.3.2. Table 2.3 shows summary statistics of the variables used in model estimation. In addition, data on pre-development and average saturated thickness at the field-level comes from McGuire et al. (2012), McGuire (2013) and McGuire (2017). These data are time-invariant and we extract the saturated thickness values from raster to the field level.

The soil characteristics included in the regression as controls are obtained from SSURGO. The national commodity crop productivity index for corn ranges from 0.01 (low productivity) to 0.99 (high productivity). Electrical conductivity is an indicator of salinity and the amount of nutrients available. Soil organic carbon is important for plant growth since it provides a source of energy for soil microorganisms and impacts nutrient availability through mineralization. The percentage of clay soil and the percentage of silty soil represent the percentage of each type of soil on the total clay, silty and sandy soils.

Table 2.3: Summary statistics for variables in the econometric analysis

	North		South	
Variables	Mean	Std. Dev.	Mean	Std. Dev.
Proportion of Corn within irrigated fields	0.61	0.49	0.24	0.42
Predevelopment Saturated Thickness (ft)	209.80	128.17	177.41	98.82
Saturated Thickness (ft)	200.71	128.67	96.22	76.41
Precipitation Normals (in)	19.02	2.93	13.15	1.21
Temperature Normals (degrees)	18.86	1.03	21.59	0.90
Crop Productivity Index Corn (prop)	0.48	0.19	0.23	0.038
Electrical conductivity	0.48	0.63	0.86	0.43
Soil organic carbon (kg/m^2)	11.36	4.45	8.96	3.71
Percentage of Clay Soil	21.95	7.87	25.83	10.76
Percentage of Silty Soil	50.17	19.41	29.33	13.61

The Figure 2.1 shows the frequency of corn planted in a 4-years period (2014-207). In general, irrigated corn is more frequently planted in the northern High Plains and the frequency declines moving south into the more arid region.

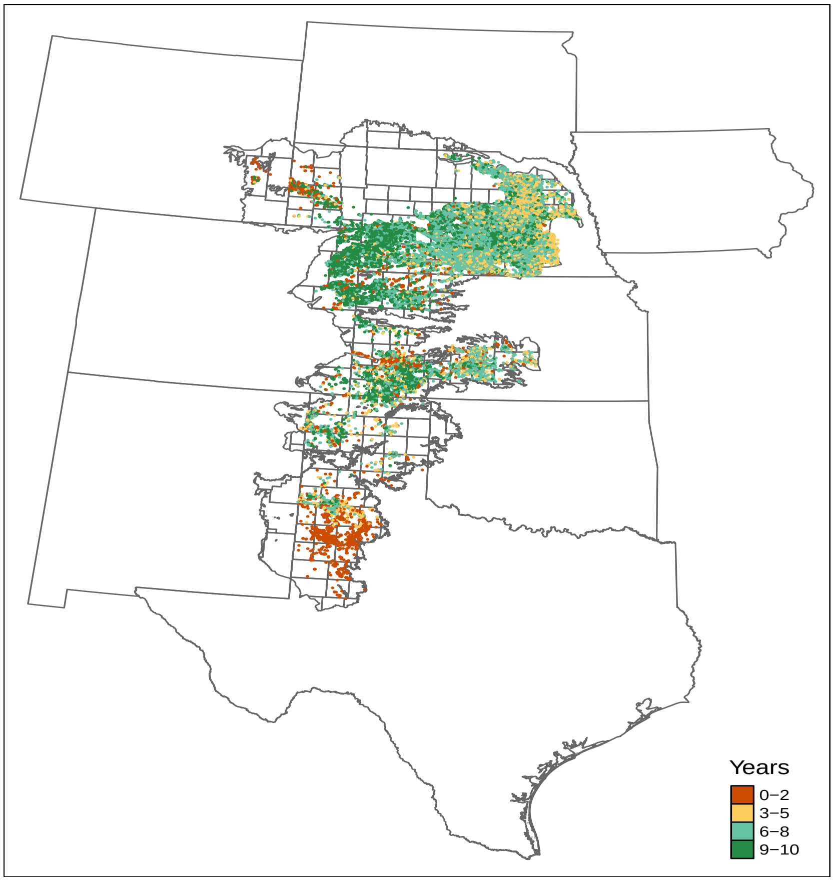

Figure 2.1: Frequency of Corn Planted in Irrigated Fields during 2008-2017

2.3.4 Impact of Saturated Thickness on Irrigated Corn Yield (c)

Econometric Model

We expect that reductions in saturated thickness may impact corn yield as less water is applied to irrigated fields. In this case, we are also concerned that potential feedback effects between saturated thickness and irrigated corn yield could bias our estimates. This occurs as farmers operating in more productive (i.e., higher yielding) lands have higher incentives to plant corn and develop irrigation which will impact groundwater stocks. To estimate the impact of saturated thickness on irrigated corn yield we follow the same empirical strategy implemented to estimate subcomponent (a.1) described in section 2.3.1. Thus, a two-stage least square (2SLS) model is estimated for irrigated corn yield using pre-development saturated thickness as an instrument.

The second-stage equation is:

$$\Upsilon_{ct}^{irr} = \beta_0 + \beta_1[(1 - D_{ct})ST_{ct} + D_{ct}K] + \beta_2 D_{ct}(ST_{ct} - K) + \\ \alpha' X_{ct} + \tau' Z_c + \delta_g + \gamma_{rt} + \varepsilon_{ct}, \tag{2.5}$$

where the dependent variable Υ_{ct}^{irr} reflects irrigated corn yield in county c in year t and $[(1 - D_{ct})ST_{ct} + D_{ct}K]$ and $D_{ct}(ST_{ct} - K)$ are linear spline functions of saturated thickness. The vector X_{ct} contatins time-variant explanatory variables. We include the contemporaneous cumulative measures for precipitation within the growing season (April 1 - September 30), the average number of growing degree days between 10°C and 30°C, and the average number of degree days greater than 32°C to isolate contemporaneous weather effects. Precipitation squared controls for nonlinear effects of precipitations on corn yield.

The vector Z_c includes several time-invariant variables. We include three long-run climate variables to describe the climate in each county: average precipitation, the average number of growing degree days between 10°C and 30°C, and the average number of degree days greater than 32°C. Hydraulic conductivity, specific yield and natural recharge account for different aquifer's characteristics in each county. The national commodity crop productivity index for corn accounts for the soil's suitability for corn. The fraction of county area in each soil group is represented by δ_g; γ_{rt} are state-by-year fixed effects for state r and year t which absorb the effects of any arbitrary shock, including technological change, variation in commodity price and groundwater laws, which is specific to a state in any given year; and ε_{ct} are idiosyncratic errors.

Data

Table 2.4 presents descriptive statistics for the variables in our model. Annual data on irrigated corn yield at the county-level are obtained from the National Agricultural Statistics Service (NASS). We construct an unbalanced panel of 141 counties over the HPA from 1982 to 2017, resulting in a total of 5,076 observations. The explanatory variables included in equation 2.5 are derived from the same sources described in section 2.3.1.

Table 2.4: Summary statistics for variables in the econometric analysis

Variables	Mean	Std. Dev.
Irrigated Corn Yield	158.79	28.58
Predevelopment Saturated Thickness (ft)	172.50	103.54
Saturated Thickness (ft)	149.72	102.40
Growing Season Precipitation (in)	16.19	5.22
Growing Degree Days	18.32	2.82
Extreme Degree Days	32.36	24.47
30-yr Avg. Precipitation (in)	16.31	3.10
30-yr Avg. Growing Degree Days (hundreds)	18.36	2.60
30-yr Avg. Extreme Degree Days	32.33	17.56
Hydraulic Conductivity (ft/day)	81.40	47.14
Specific Yield (prop.)	0.16	0.02
Natural Recharge (in)	2.62	2.13
Crop Productivity Index (prop.)	0.30	0.14

The maps in Figure 2.2 show the levels of saturated thickness in 2017 and the 1982-2017 average irrigated corn yield. In general, the spatial distribution of irrigated corn yield is related to the groundwater availability in the aquifer. Irrigated corn yields are largest in the northern High Plains and decline moving south into the more arid region.

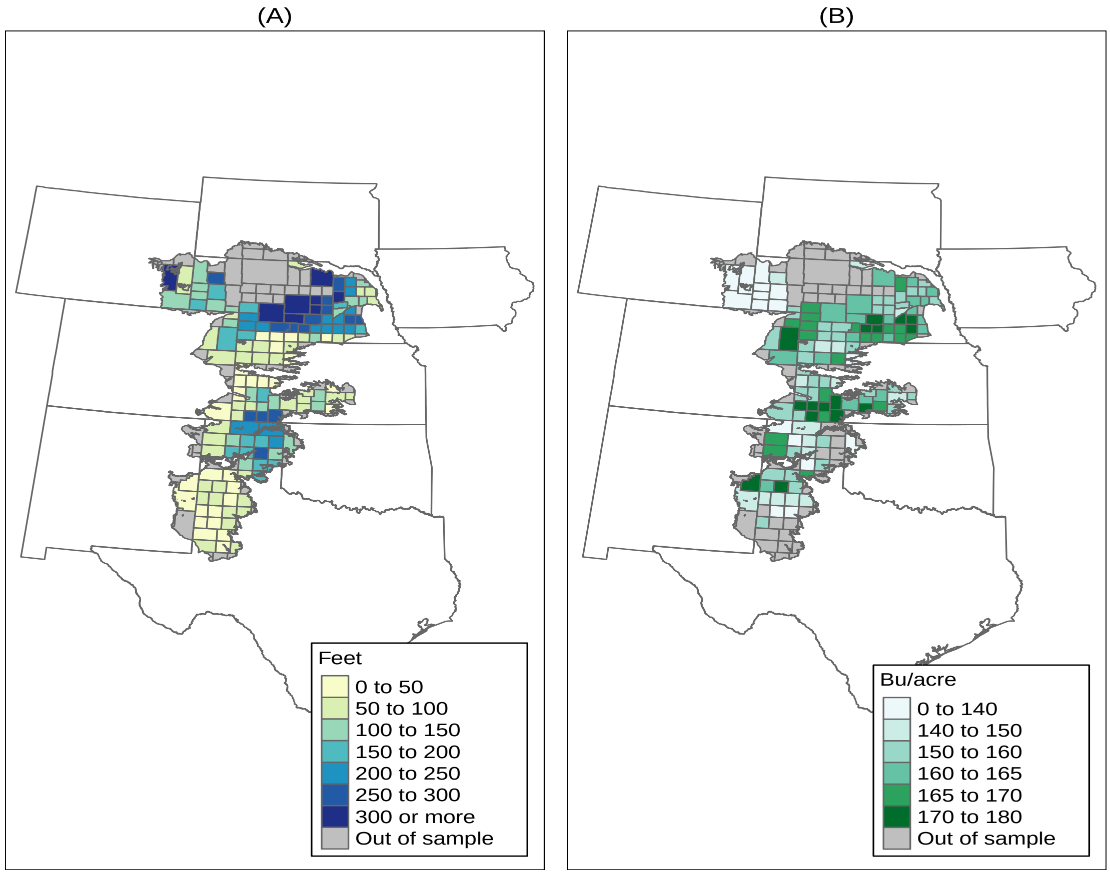

Figure 2.2: (A) Saturated thickness in 2017 (B) 1982-2017 Average Irrigated Corn Yield

2.4 Results

2.4.1 Impact of Saturated Thickness on Irrigated Acres (a.1)

The results from the 2SLS regression described in equation 2.2 are displayed in Table 2.5. The Wu-Hausman test statistic (12.48) is significant at the 1% level which provides evidence that the saturated thickness is an endogenous variable. The value of F-statistics testing the null hypothesis that the instruments are equal to zero in the first stage regressions are greater than 10 (64.92 and 105.67). Therefore, weak instruments are not a concern (Staiger and Stock, 1997).

The coefficient on the first saturated thickness linear spline indicates that when the level of saturated thickness is less than 70 ft, a 1 ft decrease in saturated thickness results in a 0.381 percentage point decrease in the cropland area that is irrigated. By contrast, when the level of saturated thickness is greater than 70 ft, a 1 ft decrease in saturated thickness results in a 0.080 percentage point decrease in the cropland area that is irrigated. As expected, the effect of a decrease in saturated thickness is larger if the initial saturated thickness is already small.

Table 2.5: 2SLS Regression Results for Impact of Saturated Thickness on Irrigated Acres

	OLS (1)	2SLS (2)
$[(1-D_{it})ST_{it}+D_{it}K]$	0.219**	0.381***
	0.085	(0.136)
$D_{it}(ST_{it}-K)$	0.072***	0.080***
	0.011	(0.013)
Growing season Precipitation	-0.075	-0.052
	(0.120)	(0.115)
Growing season Evapotranspiration	-1.367**	-1.466**
	(0.542)	(0.605)
30-yr Avg. Precipitation	-3.641***	-3.320***
	(0.949)	(0.971)
30-yr Avg. Evapotranspiration	4.376**	5.136***
	(1.646)	(1.734)
30-yr Avg. Growing Degree Days	4.942**	5.562***
	(1.412)	(1.174)
30-yr Avg. Extreme Degree Days	-0.966***	-1.021***
	(0.217)	(0.210)
Hydraulic Conductivity	0.015	0.031
	(0.044)	(0.040)
Specific Yield	133.158**	116.596**
	(56.193)	(57.889)
Natural Recharge	4.691***	4.435***
	(1.095)	(1.133)
Crop Productivity Index	-32.216**	-30.257*
	(14.986)	(15.651)
Soil groups	Yes	Yes
State-by-year FE	Yes	Yes
F-statistics for IVs in first stage	-	64.92
	-	105.67
Wu-Hausman test	-	12.48***
N	1,096	1,096

Standard errors clustered by agricultural district are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

One potential concern with the model specification in equation 2.2 is that cropland area is in the denominator of the dependent variable so it is possible that the share of cropland irrigated could change as saturated thickness changes in part due to changes in total cropland area. To alleviate concerns regarding that cropland area varies with saturated thickness, we also estimate the effect of saturated thickness on the percentage of total county acres irrigated and then scale the coefficient to represent the percentage of cropland acres irrigated. To do this, we scale the coefficients from chapter 1: $\hat{\beta}_1 \times \frac{A^{tot.aq}}{A^{cropl.aq}}$ and $\hat{\beta}_2 \times \frac{A^{tot.aq}}{A^{cropl.aq}}$, where $A^{tot.aq}$ is total area of the county overlying the aquifer, and $A^{cropl.aq}$ is the total cropland area overlying the aquifer, and $\hat{\beta}_1$ and $\hat{\beta}_2$ are parameter estimates from equation 3 in chapter 1 that uses percent of total county acres irrigated as the dependent variable. We obtain similar coefficients estimates to those shown in Table 2.5. The scaled coefficients on the first and second saturated thickness linear spline are 0.372 and 0.086.

Other covariates in the regression of percentage of cropland acres irrigated are also significant. The long-term precipitation and evapotranspiration are both significant and show the expected signs. Since precipitation and evapotranspiration are measures of natural water supply and water demand, irrigation is more valuable—and thus irrigated acres are larger—when precipitation is low and evapotranspiration is large. If drought events become more frequent due to climate change, we would expect an increase in the acreage irrigated and an increase in the extraction of groundwater for irrigation. Natural recharge is associated with increases in the percentage of acres irrigated. If a county has greater recharge, then farmers might expect less future depletion which could lead them to invest in irrigation infrastructure, increasing irrigated acres.

2.4.2 Change in Corn Production when Field is Irrigated rather than Nonirrigated (a.2)

Table 2.6 shows the estimates of the average effect of irrigation status on per acre production of corn obtained using equation 2.3. In the north region, results show that the per acre corn production in an irrigated field is on average 75.15 bushels higher than the per acre corn production in a nonirrigated field, holding other variables constant (column 1 of Table 2.6). In the southern portion of the HPA, the per acre corn production increases on average by 20.42 bushels when a field is irrigated compared to when is nonirrigated (column 2 Table 2.6). The smaller effect in the south region is mostly explained because the difference in probability of planting corn between irrigated and nonirrigated is smaller in the south.

Table 2.6: Regression Results for Impact of Irrigation Status on per Acre Corn Production

	North (1)	South (2)
Irrigation	75.62***	40.93***
	(1.381)	(3.109)
Precipitation Normals	-0.537	-2.970**
	(0.679)	(1.188)
Temperature Normals	-2.353	-1.995
	(1.435)	(2.477)
Soil-county FE	Yes	Yes
State-by-year FE	Yes	Yes
R^2	0.358	0.251
N	2,402,637	243,879

Standard errors clustered by soil-county group are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.4.3 Impact of Saturated Thickness on the Probability of Planting Corn (b)

Table 2.7 reports the regression results for the average impact of saturated thickness on the probability of planting corn in the northern and southern portions of the HPA described in equation 2.4. First, we describe the estimation results for the north region. The Wu-Hausman test statistic (9.37) is significant at the 1% level indicating that the spline saturated thickness variables are not exogenous. The values of F-statistics are greater than 10 (1,553.62 and 1,682.68) so weak instruments are not a concern.

The 2SLS coefficients on the saturated thickness linear splines show the expected sign, but only the coefficient for the first segment is significant at the 5% level (column 1 of Table 2.7). Thus, when the level of saturated thickness is less than 70 ft, a 1 ft decrease in saturated thickness decreases the probability of planting corn by 0.0028 in an irrigated field. By contrast, saturated thickness does not significantly impact the probability of planting corn in an irrigated field for levels greater than 70 ft.

Table 2.7: 2SLS Regression Results for the Impact of Saturated Thickness on the Probability of Planting Corn

	North		South	
	OLS	2SLS	OLS	2SLS
$[(1 - D_{it})ST_{it} + D_{it}K]$	0.0026***	0.0028***	0.0003	-0.0003
	(0.0004)	(0.0005)	(0.0004)	(0.0004)
$D_{it}(ST_{it} - K)$	0.0001	0.0001	0.0005***	0.0009***
	(0.00005)	(0.00006)	(0.0001)	(0.0003)
Precipitation Normals	-0.025**	-0.025**	-0.034*	-0.036*
	(0.0120)	(0.0120)	(0.020)	(0.0201)
Temperature Normals	0.028	0.034	-0.137**	-0.145***
	(0.024)	(0.024)	(0.049)	(0.051)
Crop Productivity Index Corn	-0.065**	-0.066***	0.289**	0.333**
	(0.020)	(0.020)	(0.131)	(0.138)
Electrical conductivity	-0.008	-0.008	-0.019	-0.020
	(0.006)	(0.006)	(0.017)	(0.017)
Soil organic carbon	0.001**	0.001***	-0.001	-0.002
	(0.0005)	(0.0005)	(0.0017)	(0.0015)
Percentage of Clay Soil	0.0005	0.0005	0.0018**	0.0019***
	(0.0006)	(0.0006)	(0.0006)	(0.0007)
Percentage of Silty Soil	-0.0006	-0.0006	0.0003	0.0004
	(0.0002)	(0.0002)	(0.0009)	(0.001)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
F-statistics for IVs in first stage	-	1,553.62	-	201.09
	-	1,682.68	-	27.93
Wu-Hausman test	-	9.37***	-	3.22**
N	1,170,585	1,170,585	184,934	184,934

Standard errors clustered by county are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The estimation results for the south region are shown in column 2 of Table 2.7. The Wu-Hausman test statistic (3.22) is significant at the 5% level indicating that saturated thickness is an endogenous variable. Since the F-statistics are greater than 10 (201.09 and 27.93), weak instruments are not a concern. We find that saturated thickness does not significantly impact the probability of planting corn in an irrigated field for levels below 70 ft. The predominance of cotton planted in areas where the aquifer is more depleted might explain this result. However, when the level of saturated thickness is greater than 70 ft, a 1 ft decrease in saturated thickness decreases the probability of planting corn by 0.0009 in an irrigated field.

Other covariates are also significant in the north and south regressions. However, the coefficients on other covariates do not always show the expected sign. The county fixed effects included in the regression might explain this result since the remaining variation in climate and soil variables is likely to be small within a county.

2.4.4 Impact of Saturated Thickness on Irrigated Corn Yield (c)

The results from the 2SLS regression described in equation 2.5 are presented in Table 2.8. The Wu-Hausman test statistic (3.44) is significant only at the 10% level, suggesting that we have less confidence in endogeneity bias in the yield equation than the acreage equations. The F-statistics are greater than 10 (126.74 and 455.68) so weak instruments are not a concern.

We find that when the level of saturated thickness is less than 70 ft, a 1 ft decrease in saturated thickness results in a 0.279 bushel decrease in irrigated corn yield. Similarly, when the level of saturated thickness is greater than 70 ft, a 1 ft decrease in saturated thickness decreases the irrigated corn yield by 0.023 bushels. The average irrigated corn yield is 158.79 bushels per acre, so the impact of a 1 ft decline in saturated thickness is roughly a 0.18% decrease in corn yield when initial saturated thickness is less than 70 ft and a 0.014% decrease for greater than 70 ft.

Table 2.8: 2SLS Regression Results for Impact of Saturated Thickness on Irrigated Corn Yield

	OLS (1)	2SLS (2)
$[(1-D_{it})ST_{it}+D_{it}K]$	0.221**	0.279***
	(0.076)	(0.103)
$D_{it}(ST_{it}-K)$	0.020**	0.023***
	(0.008)	(0.008)
Growing Season Precipitation	1.483*	1.505**
	(0.714)	(0.685)
Growing season Precipitation Squared	-0.050**	-0.051***
	(0.0166)	(0.016)
Growing Degree Days	-2.430	-2.419
	(1.740)	(1.653)
Extreme Degree Days	-0.358**	-0.359***
	(0.108)	(0.103)
30-yr Avg. Precipitation	-2.050*	-1.921*
	(1.150)	(1.101)
30-yr Avg. Growing Degree Days	11.971***	11.971***
	(2.628)	(2.374)
30-yr Avg. Extreme Degree Days	-0.215	-0.180
	(0.230)	(0.218)
Hydraulic Conductivity	0.004	0.013
	(0.023)	(0.023)
Specific Yield	72.295	64.553
	(48.775)	(49.094)
Natural Recharge	0.407	0.347
	(0.438)	(0.430)
Crop Productivity Index	18.267	18.775
	(17.035)	(16.661)
Soil groups	Yes	Yes
State-by-year FE	Yes	Yes
F-statistics for IVs in first stage	-	126.74
	-	455.68
Wu-Hausman test	-	3.44*
N	3,283	3,283

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Our results also highlight the role of other covariates in determining irrigated corn yield and the coefficient estimates generally follow intuition. We find that growing season precipitation positively affects irrigated corn yield but at decreasing rate. Results also show that the average number of degree days greater than 32° have a negative impact on irrigated corn yield. Furthermore, the long-run average number of growing degree days between 10°C and 30°C is positively associated with corn yield.

2.4.5 Total Impact of Groundwater Stocks on Corn Production

Decomposition of the Marginal Effect of Saturated Thickness on Corn Production

Parameters estimates from equations 2.2, 2.3, 2.4 and 2.5 are used to estimate the average impact of a 1 ft decrease in saturated thickness on production of corn per acre of cropland. Our results indicate that in the north region, a 1 ft decrease in saturated thickness decreased the average production of corn per acre of cropland by 0.296 bushels when saturated thickness is less than 70 ft (Table 2.9). Most of the impact in corn production occurs through an adjustment in irrigated acres, representing 72.6% of the total impact, while the adjustments through a reduction in the proportion of corn acres on irrigated land or reductions in corn yield represent 21.6% and 5.8%. In contrast, for levels of saturated thickness greater than 70 ft, a 1 ft decrease in saturated thickness decreased the average production of corn per acre of cropland by 0.095 bushels. A reduction of irrigated acres represents the main adjustment (82.1%) followed by a reduction in corn acres on irrigated land (9.5%) and a reduction in irrigated corn yield (8.4%).

Table 2.9: Decomposition of the Marginal Effect of Saturated Thickness on Corn Production

	Marginal Effect	
Margin of Adjustment	North	South
Saturated thickness less than 70 ft		
Irrigated acres (A)	0.215	0.156
Corn acres on irrigated land (B)	0.064	0.018
Corn yield on irrigated land (C)	0.017	0.005
Total	0.296	0.179
Saturated thickness greater to 70 ft		
Irrigated acres (A)	0.078	0.034
Corn acres on irrigated land (B)	0.009	0.038
Corn yield on irrigated land (C)	0.008	0.002
Total	0.095	0.074

In the south region, we find a smaller impact of saturated thickness on corn production. A 1 ft decrease in saturated thickness decreased the average production of corn per acre of cropland by 0.179 bushels when saturated thickness is less than 70 ft (Table 2.9). Most of the adjustments also occurs through irrigated acres (87.2%), while the adjustments through a reduction in the proportion of corn acres on irrigated land or reductions in corn yield represent 10.1% and 2.7%. Similarly, for levels of saturated thickness greater than 70 ft, a 1 ft decrease in saturated thickness decreased the average production of corn per acre of cropland by 0.074 bushels. However, the major adjustment occurs through reductions in corn acres on irrigated land, representing 51.4% of the total change in production.

Impact of a uniform 10 ft decrease in saturated thickness on corn production

The impact of a 10 ft decrease in saturated thickness on the annual corn production is estimated across the HPA. Parameters estimates from equations 2.2, 2.3, 2.4 and 2.5 are used to simulate how a uniform 10 ft decrease in saturated thickness impacts annual corn production for each county in our sample, while holding other variables constant.

The annual production of corn would decrease by 20.1, 19.3, 7.5 and 1.2 million bushels in Kansas, Nebraska, Colorado and Wyoming. These decreases in annual corn production represent 6.6%, 1.6%, 7.3% and 17.7% of the 2010-2019 average corn production across counties overlying the aquifer in each state. Similarly, the annual production of corn is expected to decrease by 1.1 and 14.6 million bushels in Oklahoma and Texas. These reductions in corn production represent 5.3% and 9.2% of the 2010-2019 average corn production across counties overlying the aquifer in each state (Figure 2.3, Panel B).

Similarly, the simulation results also show that the annual production of corn decreases on average by 48.1 million bushels across all counties in the north region. This effect represents about 3.0% of the 2010-2019 average corn production across counties overlying the aquifer in the north region. In the south region, the simulation results show that the annual production of corn decreases on average by 15.7 million bushels across all counties, which represents about 9% of the 2010-2019 average corn production across counties overlying the aquifer in the south portion.

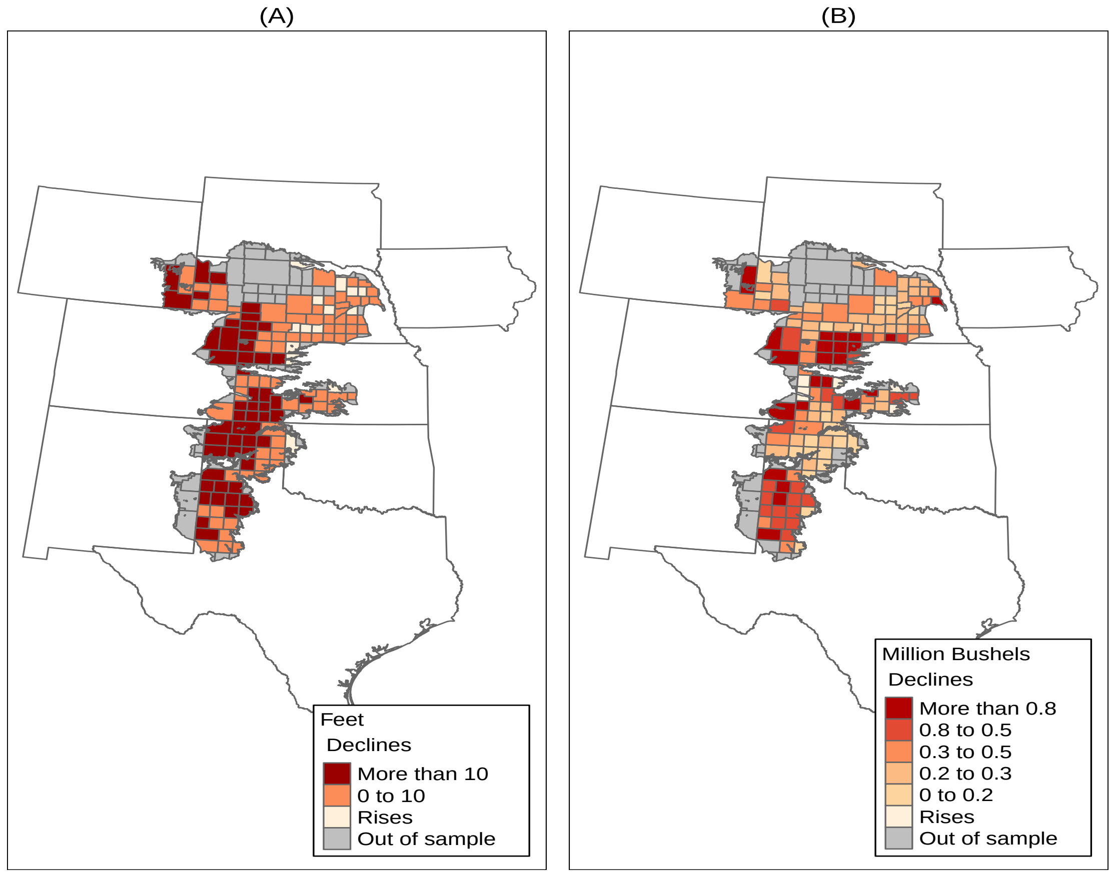

Figure 2.3: (A) 2017-2050 Projected change in ST (B) Annual change in corn production due to 10 ft decrease in ST

By 2050, 37.4% of the counties over the aquifer are projected to lose 10 ft or more of saturated thickness (Figure 2.3, Panel A). The simulation results show that the annual production of corn would decrease by 28.0 million bushels in these counties due to a 10 ft decrease in saturated thickness. This reduction in corn production represents about 5% of the 2010-2019 average corn production across these counties.

Price response to a change in the supply of corn due to a decrease in groundwater stock

We can use the change in corn production to estimate the effect of aquifer depletion on corn prices. We estimate the response of corn future prices to the projected change in corn supply due to a 10 ft decrease in saturated thickness using the corn price flexibility estimates provided by Adjemian and Smith (2012). The price flexibility is the inverse of the total demand elasticity and reflects how much price increases when supply decreases. Adjemian and Smith (2012) examine how monthly changes in World Agricultural Supply and Demand Estimates (WASDE) estimates of US corn production impact changes in the futures price for harvest delivery.

The medium-run corn price flexibility reflects the impact on the futures price of harvest delivery one year after the supply shock. Therefore, the medium-run corn price flexibility accounts for adjustments that corn consumers and producers make over time in response to a higher price. The medium-run corn price flexibility is more reasonable for our study than the short-run corn price flexibility because corn consumers and foreign producers will adjust to a persistent reduction in corn supply in the US.

The simulation results obtained in the previous section show that the annual production of corn decreases on average by 63.8 million bushels across all counties in the High Plains region when saturated thickness decreases by 10 ft. This change represents a 0.45% decrease in the average 2019-2021 US corn supply. We use the medium-run corn price flexibility of -0.60 estimated by Adjemian and Smith (2012). This flexibility implies a 0.27% price increase in response to the supply shock due to a uniform 10 ft decrease in staurated thickness in the HPA.

2.5 Conclusion

The primary contribution of this paper is to estimate how differences in the stock of groundwater affect corn production in the High Plains using observed data on groundwater stocks and corn production. Another important contribution is that we estimate crop production impact using initial groundwater conditions as an instrument to reduce potential bias from feedback effects. Lastly, we use the change in corn production to estimate effect on corn prices.

We find that the annual production of corn would decrease by 20.1, 19.3, 7.5 and 1.2 million bushels in Kansas, Nebraska, Colorado and Wyoming due to a 10 ft decrease in saturated thickness. These decreases in annual corn production represent 6.6%, 1.6%, 7.3% and 17.7% of the 2010-2019 average corn production across counties overlying the aquifer in each state. Similarly, the annual production of corn would decrease by 1.1 and 14.6 million bushels in Oklahoma and Texas, representing 5.3% and 9.2% of the 2010-2019 average corn production across counties overlying the aquifer in each state. We also find that the corn price will increase by 0.27% in response to the supply shock due to a uniform 10 ft decrease in staurated thickness in the HPA.

Chapter 3

The role of user and resource characteristics on support for collective groundwater management

3.1 Introduction

Assigning property rights to common pool resources incentivizes sustainable use. Thus, where property rights are weak or nonexistent, natural resources tend to be overused. For example, irrigated agriculture is depleting groundwater resources in many regions (Famiglietti, 2014; Richey et al., 2015) since the common pool nature of groundwater resources and the absence of well-defined property rights create limited incentives for farmers to conserve water over time. Furthermore, in most countries farmers do not pay for the cost of water they use and the lack of well-functioning water markets prevents using water more efficiently.

Our empirical analysis focuses on the Kansas portion of the High Plains Aquifer in the US where water levels are rapidly falling and threaten the viability of irrigated agriculture (McGuire, 2017; Mrad et al., 2020; Steward et al., 2013). In 1945, Kansas defined property rights to extract groundwater under the doctrine of prior appropriations. However, the system of priority has not avoided excessive depletion or the efficient allocation of water for several reasons. First, a permit to divert water could be denied only by the reasonable use rule, which allowed the use of any groundwater with an economic purpose. The reasonable use rule resulted in water rights being overappropriated. Second, there is a large cost to social capital from individuals protecting their senior rights by filing impairment complaints on their neighbors with junior rights. Third, imposing restrictions by seniority would be highly costly in the absence of a competitive water market (Burness and Quirk, 1979; Libecap, 2011). Much of the state is now closed to new appropriations and there are well-spacing requirements to prevent further overappropriation (Edwards, 2016), but there remains a challenge of reducing water use by existing water rights.

In theory, the economically efficient solution to constrain water demand would be through prices or other market-based regulations. However, the practical implementation of these solutions is difficult because of political opposition, high transaction costs and high information requirements. Incentive-based programs that compensate water users for the voluntary retirement of their water rights (e.g. Manning et al., 2020; Rosenberg, 2020; Rouhi Rad et al., 2021; Tsvetanov and Land, 2020) or groundwater extraction fees (Smith et al., 2017) have been used in an effort to conserve water. However, localized groundwater management through a bottom-up process is often more feasible than top-down regulations and garner more support among users by allowing more homogeneous stakeholders to design new rules (Guilfoos et al., 2016; Ostrom, 1990).

An example of stakeholder driven water conservation programs that has received significant interest are Local Enhanced Management Areas (LEMAs) in Kansas. A LEMA provides an alternative scheme for assigning water allocations that allows farmers to work with local and state officials to define multi-year quantity allocations for water rights within a defined boundary and the state provides regulatory oversight. The Sheridan 6 LEMA led to substantial reductions in water use with the general support among local farmers (AAAS, 2019; Deines et al., 2019; Drysdale and Hendricks, 2018). Despite general agreement about the need for groundwater conservation, the implementation of LEMAs has not been without controversy everywhere. For example, a group of water rights holders in northwest Kansas filed a case for judicial review of the district-wide LEMA to challenge the validity of the

LEMA statutory provisions.

Our paper estimates the role of resource and user characteristics in determining the preferences of farmers for reductions in groundwater use through a LEMA. We exploit unique data obtained from consequential stated preference surveys to gain insights about how characteristics of the farmers and water rights and attributes of the aquifer affect preferences of farmers for groundwater management. The surveys are consequential because they were conducted in cooperation with the Groundwater Management Districts (GMDs) and thus, farmers were aware that their responses could influence future actions by their GMD. Carson et al. (2014) argue that respondents have an incentive to respond honestly as long as they perceive a positive probability of their response having some consequence on real-world outcomes. The consequentiality of our survey means that it is likely to reveal true preferences and not suffer from hypothetical bias (Vossler et al., 2012).

Using an interval regression model, we find that farmers located in areas where the aquifer is more depleted support larger reductions in groundwater use through the establishment of a LEMA. However, ignoring the effect of other factors such as characteristics of the farmers can prevent collective action efforts since farmers who strongly agree that water rights are a private property, landlords and those who irrigate a larger proportion of their farm are less supportive for reductions in water use. Therefore, local groundwater managers might need to devote special attention to these types of farmers to garner more support to establish a LEMA. We further evaluate farmers' preferences for the methods of assigning water allocations using a rank-ordered probit model. We find that there is no method that is preferred by a majority of farmers and there is no clear evidence of what are the main factors determining the preferred method of assigning water allocations, which can make it difficult for groundwater managers to identify which method is more likely to be considered fair by farmers.

Our paper also contributes to the extensive literature focused on the understanding of factors that facilitate or prevent collective action for the management of common pool resources (Baland and Platteau, 1996; Ostrom, 1990; Wade, 1988). However, rather than relying on case studies or laboratory experiments (Fischer et al., 2004; Margreiter et al., 2005; Suter et al., 2012) in developing countries, we exploit real-world data from surveys conducted in a developed country. Lastly, previous studies suggests that the number and heterogeneity of resource users affect contracting costs and prevent agreement on resource extraction (Coase, 1960; Wiggins and Libecap, 1985). Ayres et al. (2018) provide empirical evidence that contracting costs over groundwater governance regimes in California groundwater basins rise with basin size, the number and heterogeneity of users, and variance in resource characteristics. Different from Ayres et al. (2018), our study includes a richer set of users' characteristics to explore which characteristics of the resource and users are more relevant for creating heterogeneity that prevents agreement on water conservation programs.

3.2 Background

The agricultural economy of western Kansas is dependent on groundwater which is the primary source of water for irrigation. In 2015, groundwater provided 96% of irrigation water and irrigated agriculture was the largest consumer of water (Dieter et al., 2018). Western Kansas is a semiarid region with high evapotranspiration, where natural recharge rates are lower than the extraction rates of groundwater for irrigation, leading to persistent aquifer depletion (Sophocleous, 2005). From pre-development to 2015, the average water level has decreased by 26.2 feet in Kansas (McGuire, 2017). This stressed aquifer condition raises concerns to the long-term viability of irrigated crop production and associated industries (Deines et al., 2020; Mrad et al., 2020; Scanlon et al., 2012). Steward et al. (2013) show that reducing water use now by 20%, Kansas could extend the time to peak production to the 2070's. But avoiding any sort of peak altogether would require drastic measures.

The State of Kansas enacted the Water Appropriation Act in 1945, establishing the doctrine of prior appropriation to regulate groundwater rights. This act states that all the groundwater is owned by the state and dedicated to the use of citizens as specified in the state's water appropriation act (K.S.A. 82a-701)[1]. To obtain a right to divert water, for any

[1] https://agriculture.ks.gov/docs/default-source/statues-water/kswaterappropriationact82a_701.pdf?sfvrsn=bbdeaac1_32

purpose other than domestic use, a prospective groundwater user must obtain a permit from the Chief Engineer of the Division of Water Resources (DWR) of the Kansas Department of Agriculture (KDA). Each water right is assigned a maximum annual quantity of water that can be extracted and a specified place of use. The prior appropriation doctrine embodies the concept of "first in time - first in right." Thus, the date that the permit is authorized defines the priority of the right, with older rights having seniority. Therefore, if pumping by a junior water right holder impairs the ability of a senior water right holder to exercise its right, then the junior can be required to reduce withdrawals. Only 334 permit applications were filed from 1945 to 1950. However, consistent with the adoption of new technology to pump water in Kansas, the number of permit applications increased to 5,730 in the 1950's and to 6,433 in the 1960's (Peck, 2006). Moreover, a farmer's decision to obtain a permit to divert water for irrigation, was influenced by the adoption decisions of his or her peers (Sampson and Perry, 2019).

By the late 1960s, water-level declines had become evident in many areas of the state as consequence of the rapid and substantial increase in groundwater for irrigation. The system of priority was not able to avoid excessive depletion for several reasons. First, a permit to divert water could be denied only by the reasonable use rule, which allowed the use of any groundwater with an economic purpose. As an example, groundwater permits were obtained by almost anyone who requested them during the 1970's (Pfeiffer and Lin, 2012). The reasonable use rule resulted in water rights being overappropriated. Second, there was a large cost to social capital from individuals protecting their senior rights by filing impairment complaints on their neighbors with junior rights. Third, imposing restrictions by seniority would be highly costly in the absence of a competitive water market (Burness and Quirk, 1979; Libecap, 2011).

In response to depleting groundwater resources, a new legislation was passed in 1972 to enable the formation of groundwater management districts (GMDs) (Peck, 2006). As a result, five GMDs were created to provide some degree of local control over the groundwater depletion problems. All districts correspond to major portions of the HPA where groundwater is mainly used for irrigation (Figure 3.1). GMDs have the authority to establish management plans and create and enforce policies subject to the approval by the Chief Engineer of the Kansas Division of Water Resources, but they have mainly implemented policies limiting new appropriations. This includes minimum well spacing requirements and closing the district to further drilling. However, GMDs had never restricted water use on existing wells before 2013.

In 2012, GMDs were granted the authority to recommend the approval of Local Enhanced Management Areas (LEMAs). The GMD board of directors, elected water right owners (usually farmers) representing different counties within a GMD, develops a LEMA proposal which is approved by the Chief Engineer. A LEMA proposal includes the proposed restrictions on water use, sanctions for non-compliance, and could include other types of measures such as allowing trading of water rights within the LEMA. Once the LEMA proposal is considered acceptable by the Chief Engineer, an initial public hearing is held to go over initial questions to discuss whether a LEMA meets specific statutory requirements. Subsequent hearings are held to gather further input from the public. Once the LEMA is implemented, it is monitored and enforced by the Kansas Department of Agriculture.

There are currently three LEMAs implemented in western Kansas. The first LEMA became effective in the 2013 crop year in a High Priority Area of Sheridan County (an area roughly 6x15 miles) in GMD4. The Sheridan 6 LEMA set a goal of reducing water withdrawals by 20% over the five-year (2013-2017) period relative to 2002-2012 levels. The reduction was implemented by restricting irrigators to an allocation of 55 inches per authorized acre over a 5-year period. In 2017, stakeholders voted to renew the Sheridan 6 LEMA and a new allocation was approved for the 2018-2022 period[2]. Drysdale and Hendricks (2018) find that farmers reduced water use by 26% due to the restrictions on water use imposed by the LEMA primarily by reducing irrigation intensity on existing crops and with minimal reductions in irrigated acres.

The second LEMA is the GMD4 district-wide LEMA in Northwest Kansas that began in 2018[3]. This district-wide LEMA sets a 5-year allocation for pumping, where the allocation

[2] https://agriculture.ks.gov/divisions-programs/dwr/managing-kansas-water-resources/local-enhanced-management-areas/sheridan-county-6-lema

[3] https://agriculture.ks.gov/divisions-programs/dwr/managing-kansas-water-resources/

is defined for each township (approximately 6 miles $\times$ 6 miles) in the district. The LEMA was ultimately approved and implemented in 2018 but was not without controversy. After two public hearings held by the Chief Engineer, a group of water rights holders filed a case for judicial review of the LEMA. Petitioners challenged whether the reductions in water use can be made without those cuts being based on priority and generally challenged the validity of the LEMA statutory provisions. In October 2019, the district court upheld the authority of the GMD to implement a LEMA.

Recently, the Wichita County LEMA was approved to reduce water use by 25% over the five-year (2021-2025) period relative to 2009-2015 levels[4]. The reduction was implemented by restricting each point of diversion to an allocation of 25% of historical usage defined as the average quantity of authorized water used by a point of diversion during the 2009-2015 period.

3.3 Data

3.3.1 Preferences for Irrigation Water Management

We conducted a survey to measure preferences of farmers for mandatory reductions in water use through the establishment of a LEMA. The survey was sent to every individual who either filed a water use report or owns a water right in GMD 3 in the spring of 2019, and in GMD 1 in the spring of 2021 (Figure 3.1). In GMD 3 (GMD 1), the survey was mailed to 3,961 (832) individuals and a total of 706 (184) responded to the survey (18% (22%) response rate), but only 653 (170) surveys were usable because of incomplete answers. The surveys are consequential because they were conducted in cooperation with GMDs and thus farmers were aware that their responses could influence future actions by their GMD. The consequentiality of our surveys means that it is likely to reveal true preferences and not suffer from hypothetical bias (Vossler et al., 2012).

local-enhanced-management-areas/gmd4-district-wide-lema

[4] https://agriculture.ks.gov/divisions-programs/dwr/managing-kansas-water-resources/local-enhanced-management-areas/wichita-county-lema

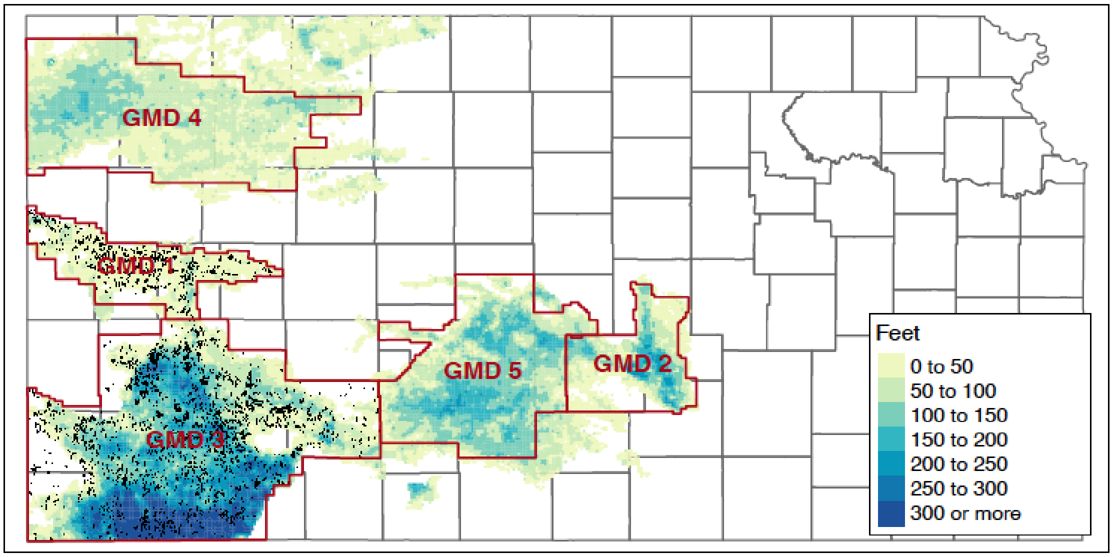

Figure 3.1: Average 2017-19 saturated thickness and irrigation wells of survey respondents indicated in black

In the first part of the survey, respondents were asked about their preferences regarding LEMAs characteristics. The two main questions we analyze ask each respondent to indicate the best and worst options for how much water use should be reduced on average in the area where he irrigates and the best and worst methods to use when calculating the allocated quantity of water use for each water right within an area. This latter question differs between the survey conducted in the GMD1 and GMD 3. While ideally the survey questions could have been the same in both districts and conducted in the same year, we felt that it was important to work with each GMD board of directors on the survey design and this caused some differences in questions.

Figure 3.2 shows question 1 on the survey where the water reduction goal is expressed as a percent reduction in area-wide average use. This does not necessarily mean that each water right in the area would be required to reduce water use by that percentage. How much each water right must reduce water use depends on the method of assigning the allocations described in question 2. Data from question 1 are not continuous but the underlying variable (the percentage) is technically measured on a ratio scale (e.g., 0% has a meaning). We only use the answers for the best option as a dependent variable in the econometric model.

One potential method to conserve groundwater is to use a Local Enhanced Management Area (LEMA) to define multi-year quantity allocations for water rights within a defined boundary. The following questions ask your preferences over possible LEMA characteristics.

1. Indicate how much water use should be reduced **on average** in the area(s) where you irrigate (an "area", for example, could be defined as a township). (Note that 0% means no change in average water use, and 10% means a 10% reduction in use.)

	0%	2.5%	5%	10%	15%	20%	25%	>25%
Best Option	☐	☐	☐	☐	☐	☐	☐	☐
Worst Option	☐	☐	☐	☐	☐	☐	☐	☐

Figure 3.2: Question 1 for GMD 1 and GMD 3.

Figure 3.3 shows how preferences for groundwater reduction vary among respondents. Most of them indicate that they prefer no change (0%) in average water use as the best option. This implies that 33.1% of the total respondents would not support the LEMA implementation. However, 35.5% support a reduction between 2.5 and 10% while 31.4% support a reduction of 15% or more.

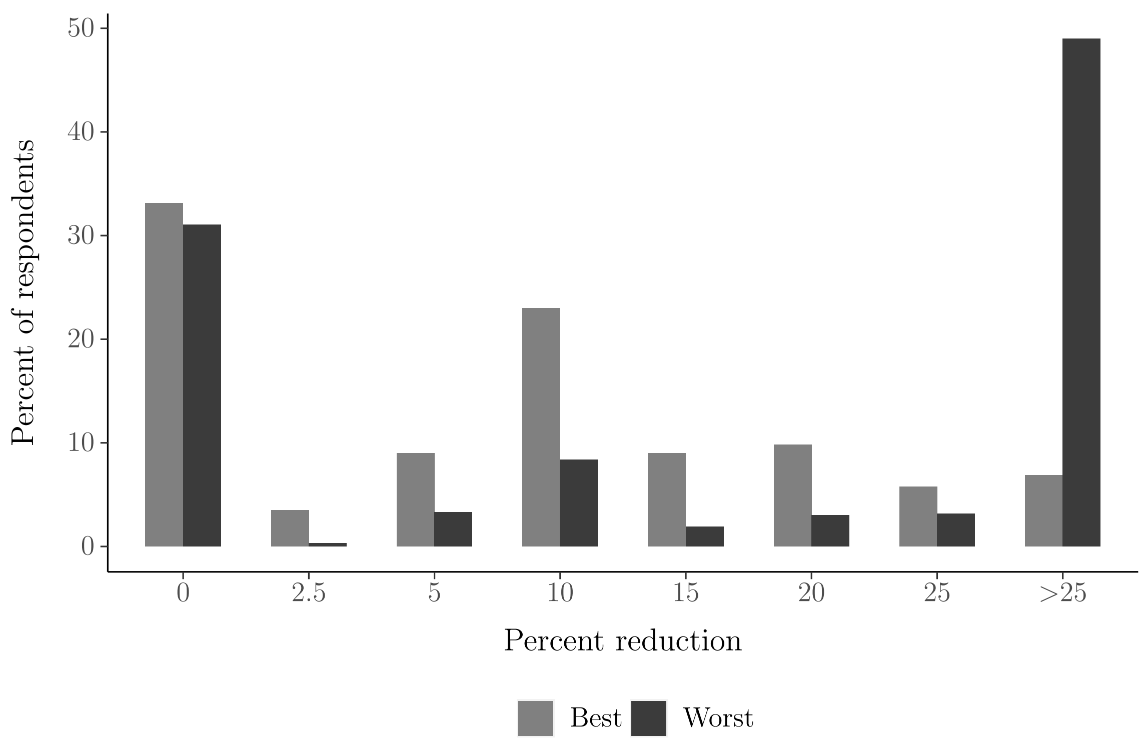

Figure 3.3: Best and worst option for water reduction.

Panel (a) of Figure 3.4 shows the question related to the method of assigning allocations in GMD 1 and panel (b) shows the analogous question for GMD 3. Each method of assigning allocations described in the second question can be implemented to give the same area-wide average reduction in water use, but the volume of water that each water right is allocated depends on the method used to assign these allocations (Table 3.1).

12. Indicate below what you think is the 1st best, 2nd best, and worst option for the method of assigning allocations if a LEMA were to be implemented in the area where you irrigate.

	Percent of Historical Water Use	**Percent of Water Right** Authorized Quantity	**Inches** using **Average** Irrigated Acres	**Inches** using **Maximum** Irrigated Acres	**Inches** using **Water Right** Authorized Acres
1st Best	☐	☐	☐	☐	☐
2nd Best	☐	☐	☐	☐	☐
Worst	☐	☐	☐	☐	☐

(a) GMD 1

For the following questions, assume that a LEMA is going to be implemented in your area(s).

2. Indicate the best and worst methods to use when calculating the allocated quantity of water use for each water right within an area.

	Percent reduction from an individual's historical use.	Senior water rights receive a larger allocation.	Every water right in area receives the same allocation (inches/acre).
Best Option	☐	☐	☐
Worst Option	☐	☐	☐

(b) GMD 3

Figure 3.4: Question 2.

To pool responses from the two GMDs survey, we only consider the best and the worst options and we combine the second question into three methods (Table 3.1). Thus, individuals are asked to select their best and worst options out of a set of three different methods to use when calculating the allocated quantity of water use for each water right. Therefore, a complete ranking of alternative is given, and rank-ordered data are obtained.

Table 3.1: Method of assigning allocations

Consolidated Allocation Method	GMD Survey	Method Description
Percent of Historical Water Use (Historical)	GMD 1 & GMD 3	Percent reduction from an individual's historical use
Every water right in area receives the same allocation (inches/acre) (Inches)	GMD 1	Inches using average irrigated acres
	GMD 1	Inches using maximum irrigated acres
	GMD 1	Inches using water right authorized irrigated acres
	GMD 3	Every water right in area receives the same allocation
Water Right	GMD 1	Percent of water right authorized quantity
	GMD 3	Senior water rights receive a larger allocation

Figure 3.5 shows that there is no method that is preferred by a majority. However, we can observe that 47% of the respondents indicate "Inches" as the best alternative while about 38% selected "Water right" as the worst alternative.

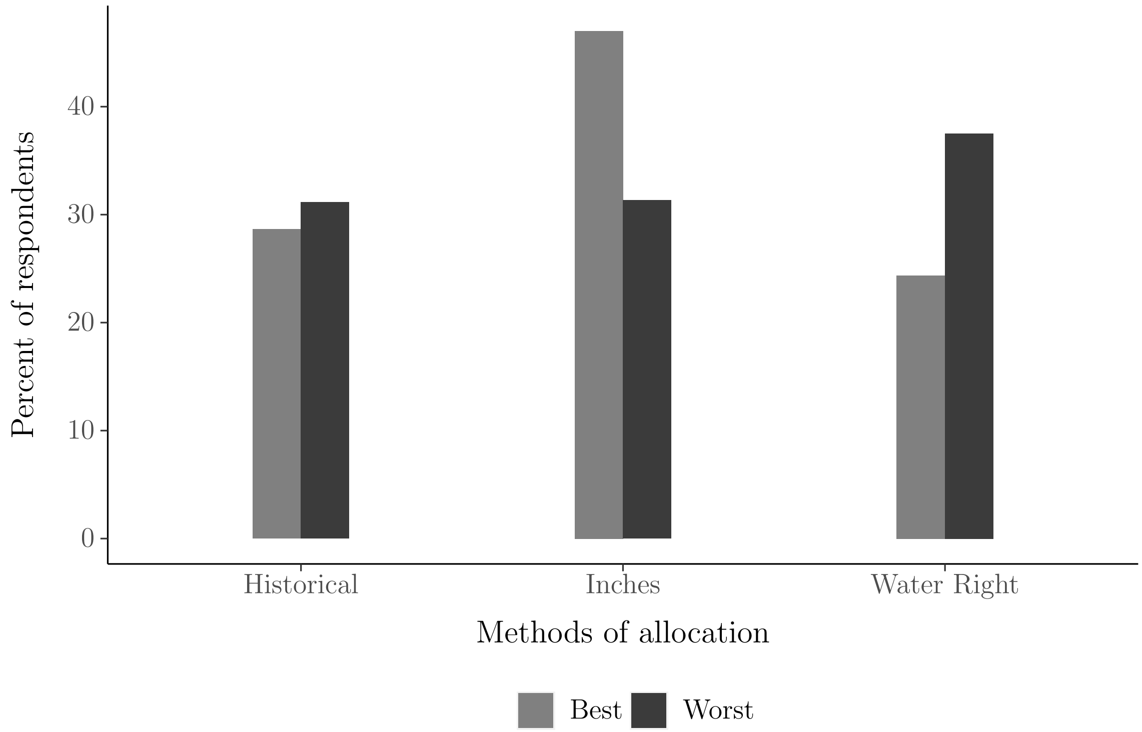

Figure 3.5: Best and worst methods to calculate the allocated quantity of water use for each water right.

3.3.2 Explanatory Variables

The explanatory variables included in the econometric models and their sources are described next. Summary statistics for the explanatory variables are displayed in Table 3.2.

Aquifer Characteristics

Saturated thickness of the aquifer is a measure of the vertical height of the aquifer and, thus, reflects the resource stock at a given location. Saturated thickness and the depth to water table are interpolated from monitoring well data provided by KGS. We include wells with average winter water level (December to April 15) measurements from 2000 to 2019. We use the inverse distance weighted (IDW) interpolation method to predict values in space where no measurements have been made. IDW measures values at unmeasured locations using the values of the nearest surrounding measured locations, where each point has an influence on the unmeasured value that diminishes as a function of distance. Thus, weights assigned to data points are proportional to the inverse of the distance (between the data point and the prediction location) raised to the power value p. We set $p = 2$, a common value used in practice, which means that the weights for distant points decrease rapidly. The 2017-2019 average saturated thickness across wells in our sample is 122.80 ft with a maximum of 377.63 ft, while the 2017-2019 average depth to water across wells is 172.57 ft with a maximum of 313.84 ft (Table 3.2).

Hydraulic conductivity is a measure of the rate at which water can move laterally to a well. The hydraulic conductivity data are obtained from KGS. This data set is time invariant at the section level. We obtain well-level hydraulic conductivity data by extracting the value at the location of each well. The average value of hydraulic conductivity of the wells managed by the respondents is 77 ft/day (Table 3.2).

Natural recharge is the seepage of water into an aquifer, not including return flows from irrigation. Data are obtained from Houston et al. (2013) and extracted from a raster using well location. In general, natural recharge from precipitation is low in Kansas but there is significant variation within the state (Sophocleous, 2005). The average natural recharge in our sample is 1.83 inches (Table 3.2), with an average of 0.99 inches in GMD 1 and 2.07 inches in GMD3.

In addition, we use the parameter estimates from chapter 1 to estimate how the change in saturated thickness from 2000 to 2019 impacted the returns per acre of land that was initially irrigated[5]. As table 3.2 indicates, the returns per acre of land that was initially irrigated decreased on average by \$17.76 in our sample, with a maximum decrease of \$87.33.

[5] We consider the returns on 1 acre that was irrigated in 2000 with returns equal to $R^{irr}_{2000}(ST)$, where $R^{irr}_{2000}(ST)$ is the irrigated cash rental rate in 2000. The same acre in 2019 has returns per acre of land that was initially irrigated equal to $\left[\frac{\Phi^{irr}_{2019}(ST)}{\Phi^{irr}_{2000}(ST)} \times R^{irr}_{2019}(ST) + \left(1 - \frac{\Phi^{irr}_{2019}(ST)}{\Phi^{irr}_{2000}(ST)} \times R^{non}_{2019}\right)\right]$, where $\Phi^{irr}_{2019}(ST)$, $\Phi^{irr}_{2000}(ST)$ are the proportion of acres in the county that are irrigated, and $R^{irr}_{2019}(ST)$, $R^{non}_{2000}(ST)$ are the irrigated and nonirrigated cash rental rates. Thus, the change in returns per acre of land that was irrigated in 2000 is equal to $\left[\frac{\Phi^{irr}_{2019}(ST)}{\Phi^{irr}_{2000}(ST)} \times R^{irr}_{2019}(ST) + \left(1 - \frac{\Phi^{irr}_{2019}(ST)}{\Phi^{irr}_{2000}(ST)} \times R^{non}_{2019}\right)\right] - R^{irr}_{2000}(ST)$.

Table 3.2: Summary Statistics for Variables Used in the Econometric Models

	N	Mean	Std. Dev.	Min	Max
Aquifer Characteristics					
Saturated thickness (ft)	809	122.80	69.58	6.74	377.62
Change in saturated thickness 2000-2019 (ft)	749	-26.73	12.96	-64.37	-1.47
Depth to water (ft)	809	172.57	54.10	23.16	313.84
Hydraulic conductivity (ft/day)	793	77.00	24.81	0.00	119.50
Natural Recharge (in)	817	1.83	1.65	0.00	8.25
Change in returns to land ($/acre)	646	-17.76	18.72	-87.33	-0.91
Water Use, Water Rights and Farm Characteristics					
Historical intensity of irrigation (in)	764	-0.22	2.50	-18.07	11.21
Density of wells	819	25.70	12.30	0	89.97
Proportion of farm irrigated	655	0.42	0.31	0	1
Total cropland (acres/′000)	694	3.19	5.45	0	73.60
Average water right number (′000)	822	0.30	0.16	0	1
Crop Productivity Index (fraction)	822	0.27	0.10	0.08	0.52
Individual Characteristics					
Proportion of acres owner-operator	626	0.41	0.43	0	1
Proportion of acres tenant	626	0.27	0.38	0	1
Proportion of acres local landlord	626	0.22	0.40	0	1
Proportion of acres not local landlord	626	0.10	0.30	0	1
Expect younger family to farm (binary)	737	0.58	0.49	0	1
Proportion of income from farming	703	0.68	0.33	0	1
Farmer age	735	67.35	13.94	25.00	97.00
High education level (binary)	741	0.49	0.50	0	1
Water rights are a private property right					
Neutral, disagree or Strongly disagree	745	0.29	0.46	0	1
Agree	745	0.31	0.46	0	1
Strongly Agree	745	0.40	0.49	0	1

Water Use, Water Rights and Farm Characteristics

Further information is obtained matching respondents to records in the Water Information Management and Analysis System (WIMAS) data set from Kansas Geological Survey (KGS). To link the data, we used a mailing address list obtained from KDA where each address has an identifying number attached to it that can be matched to well records in the WIMAS data. WIMAS provide spatial, well-level data on water use, water rights and irrigated acres. The period of WIMAS data that we use in this study is between 2000 and 2019. We calculate the 2000-2019 average of each variable at the well-level in WIMAS and then we aggregate them to the respondent level. Historical intensity of irrigation is defined as the difference between the water applied per acre and the average water applied per acre in the respective township. On average, respondents in the survey apply close to the average applied in the township (Table 3.2). We also calculate the historical density of wells as the average number of neighboring wells in a radius of 2 miles that each well has. Table 3.2 shows that each well that the respondent manages has on average about 26 neighboring wells. Finally, there are data on the water right number which is a sequential priority number assigned to each right as water right applications are received by KDA-DWR. The lower the number, the more senior the right. For each respondent we calculate the average water right number among his wells. For ease of interpretation, we divide the average water right number by its maximum value. Therefore, an average water right of 1 is the most junior and closer to 0 is more senior.

In the survey, respondents were asked to report the proportion of acres that are irrigated in the farm and the total acres of cropland. The summary statistics reveal that the proportion of acres that are irrigated is on average 0.43 across respondents, and the average size of a farm in terms of cropland is 3,190 acres.

The national commodity crop productivity index for corn and soybeans is obtained from the Soil Survey Geographic database (SSURGO). This variable ranges from 0.01 (low productivity) to 0.99 (high productivity), with an average value in our sample of 0.27 (Table 3.2).

Individual Characteristics

The survey also includes questions about characteristics of the farmers. They reported the proportion of acres associated with water rights under different respondents' role (e.g., owner-operator, tenant and landlord). Using this information and Zip code boundaries obtained from the Data Access and Support Center (DASC) created by the State of Kansas, we classify landlords as local if the mailing address was in one of the counties of western Kansas. As shown in Table 3.2, on average the proportion of acres under the owner-operator role is 0.41, while the proportion of acres under tenant, local landlord and non-local landlord roles is 0.27, 0.22 and 0.10.

Respondents reported whether they expect a younger family member to continue farming and the proportion of their household income that comes from farming. On average, the proportion of respondents that expect a younger family member to continue farming after they retire is 0.58. Similarly, the proportion of the total household income that comes from farming is 0.68 indicating a high dependency on agricultural production. Additionally, there are data available on respondents' age and education. The average age across respondents is 67 years and less than half of them have a bachelor or graduate degree. Respondents also stated their degree of agreement with different statements related to groundwater management. In particular, we analyze whether they agree or not with the following statement: "Water rights are a private property right". As Table 3.2 shows about 70% of them agree or strongly agree with this statement.

3.4 Empirical Specification

3.4.1 Econometric Model of Preferred Reduction in Water Use

The preferences of farmers for a reduction in water use through a LEMA are analyzed in this section. The question 1 (best option) in the survey provides the data for this analysis. As we described before, data from question 1 is not continuous but the underlying variable (the percentage) is technically measured on a ratio scale (e.g., 0% has a meaning). Thus, the data are converted to interval censored data to implement an interval regression model. As an alternative to interval regression, we can create preferred water use reduction brackets and consider this variable as an ordered categorical outcome to be estimated using an ordered logistic or probit model. However, interval regression provides a more convenient interpretation of the marginal effect for our study. The marginal effect in the interval regression reflects the change in the preferred reduction in water use, whereas the marginal effect of the order logit or probit reflects the change in the probability of selecting a given bracket.

Interval regression can fit models for data where each observation represents interval data, left-censored data, right-censored data, or point data. Thus, it requires two variables—a lower and upper bound for each observation, to represent the values of the response variable. Table 3.3 shows how we specify the bounds for each category in the survey. Together they represent the range in which the value falls. This estimation method is a generalization of the Tobit model for data observed in intervals (Cameron and Trivedi, 2010). The interval regression model assumes normality and uses maximum likelihood to obtain the parameter estimates.

Table 3.3: Dependent variable for the interval regression

Reduction in water use	Lower bound	Upper bound	Type of data
0%	.	2.5	left-censored
2.5%	2.5	5	interval
5%	5	10	interval
10%	10	15	interval
15%	15	20	interval
20%	20	25	interval
25%	25	25	point
$> 25\%$	25	.	right-censored

The estimating equation for the preferred reduction in water use for farmer i is:

$$Y_i = \beta_0 + \beta_1[(1 - D_i)ST_i + D_iK] + \beta_2 D_i(ST_i - K) + \gamma' H_i + \theta' F_i + \alpha' X_i + \varepsilon_i \qquad (3.1)$$

where Y_i is the best percent reduction in water use, K is the location of the spline knot, and

$$D_{it} = \begin{cases} 0 & \text{if } ST_{it} < K \\ 1 & \text{if } ST_{it} \geq K. \end{cases}$$

We assume a nonlinear relationship between saturated thickness and the preferred reduction which is represented using linear spline regression.

A linear spline is a piecewise linear function that fits a line in each segment of the saturated thickness space defined by the knot while requiring continuity at the knot (Harrell, 2001). ST_i is the average 2017-2019 saturated thickness across all wells that farmer i manages, $[(1-D_i)ST_i + D_iK]$ and $D_i(ST_i - K)$ are linear spline functions of saturated thickness. Based on exploratory analysis of our data and previous studies, we allow for one spline knot location ($K = 70$). The term H_i is a vector of control variables that include other location-specific hydrologic characteristics of the aquifer, F_i is a vector of variables capturing water use, water right and farm characteristics, and X_i is a vector that includes individual characteristics. A detail description of these variables is provided in the next section. $\beta_0, \beta_1, \beta_2, \gamma', \theta', \alpha'$ are the parameters to be estimated. The term ε_i is a random error term.

As a separate specification, we include the change in returns per acre of land that was initially irrigated due to a change in saturated thickness from 2000 to 2019 in equation 3.1 but we drop saturated thickness and depth to water variables because the mechanism through which they affect the preferred reduction is through the change in returns.

3.4.2 Expected Signs of Coefficients in Model of Preferred Reduction in Water Use

Saturated thickness is a measure of the groundwater stock and affects the extraction rate of wells such that as saturated thickness decreases, well yield decreases. Well yield imposes a constraint on the rate at which water may be pumped and applied for irrigation affecting farmers' economic benefits. We allow a nonlinear relationship between saturated thickness and preferences for water reduction since when saturated thickness is large the economic gains from imposing pumping restrictions can be negligible (Foster et al., 2017). This different impact might create different incentives across farmers to support a LEMA. Intuitively, when saturated thickness is above a certain level, a decrease in saturated thickness may have minimal effect on producer behavior since well yield is not a binding constraint. However, once the saturated thickness declines below a certain level, the well yield may become constraining and farmers may adjust their behavior by either reducing irrigated acres or reducing irrigation intensity. We expect farmers with less saturated thickness to be more concerned about groundwater scarcity and its impact on their production. Thus, they would expect larger benefits from groundwater management. Consequently, we expect they would prefer larger reductions in groundwater use.

Reductions in groundwater availability also affect farmers' economic benefits through increasing pumping costs. Thus, to capture the impact of reduced groundwater stock on pumping cost, we include the depth to water table (included in H_i). The pumping cost is greater for farmers with greater depth to water, so these farmers might experience larger benefits from groundwater management. In the alternative model specification, we include the change in returns per acre of land that was initially irrigated but we drop saturated thickness and depth to water because the change in returns is the main mechanism through which they affect the preferred reduction in water use. We expect gains from the implementation of a LEMA may be larger where the returns to land are declining more rapidly.

Other location-specific hydrologic characteristics of the aquifer are also included in the H_i vector to explain differences in the preferred reduction in water use. The change in saturated thickness between 2000 and 2019 controls for changes in the stock of groundwater available for use and reflects the depletion rate. In places where the depletion rate is larger, farmers might be more concerned with future water availability and be more likely to support larger reductions in water use.

Like saturated thickness, wells with higher hydraulic conductivity have higher well yield, which would reduce farmers support for water reductions. However, hydraulic conductivity is also a measure of how shared the aquifer is in each location. Thus, higher hydraulic conductivity may also increase farmers preferences for groundwater management if they believe other users' pumping is affecting the future groundwater stock more than his own pumping. Natural recharge controls for different expected rates of aquifer depletion that affect expectations of future aquifer stocks. We expect that farmers located in portions of the aquifer with lower recharge rates would benefit more from groundwater management and are more likely to support reductions in water use.

The vector F_i includes water use, water rights and farm characteristics that might affect the preferred reduction in water use. The proportion of acres irrigated of the total farm acres, the total cropland in the farm and the historical intensity of irrigation tend to capture the importance of the aquifer for the farmer. These variables could have either a positive or a negative impact on farmers' preferences for water reduction. For example, farmers who apply more water may be more willing to support management to conserve water for the future, but also, they may have the most to lose in the short run from a restriction on water use.

Similar to hydraulic conductivity, well density also reflects the spatial extent to which one farmer's pumping affects his neighbors pumping. As well density increases, it is more likely that groundwater pumping by neighbors affects a farmer's pumping through overlapping cones of depression which reduce the water table and increase pumping cost. Thus, gains from the implementation of a LEMA may be larger where well density is larger. We also include the water right number to reflect the seniority of the water right. We expect that more senior water right holders would prefer lower or no reduction in water use because they can protect their right based on seniority. Finally, to capture soil characteristics we include national commodity crop productivity index for corn and soybeans. If more productive land increases the returns from irrigation, then farmers could either support larger reductions in water use to ensure future water availability or support smaller reductions because of its impact on the short-term returns. Therefore, the expected sign of the coefficient on soil productivity is indeterminate.

The last set of variables we include in the model are individual characteristics (X_i). Differences in preferences for water reduction could also differ across farmers due to how they discount future benefits and how much they rely upon groundwater to sustain their farms. We expect that farmers who are owner-operators are more likely to support a LEMA compared with tenants because owner-operator farmers might have a greater incentive to preserve future economic value. Similarly, landlords might be less concerned about groundwater management since they tend to have a more diverse source of income. We include two additional variables, a dummy variable to capture whether a younger family member is expected to continue farming and the percent of income from farming to further measure the farmer's dependence on the aquifer. As the farm is more dependent on the groundwater, we expect higher preferences for water reduction to extend the life of the aquifer.

We expect that more educated farmers are more likely to support larger reductions in water use through a LEMA. When farmers have a good understanding of the characteristics of the aquifer and how their actions affect it, they may perceive lower costs of investing time to participate in the design of a LEMA and greater gains from management. We also include farmer's age, but the expected sign might be positive or negative. Older farmers may not value conservation that creates value beyond their lifespan. On the other hand, older farmers may be less concerned with current economic impacts of reductions and place greater value on preserving the resource for future generations.

Lastly, to capture differences in beliefs and ideology among farmers we include a variable that captures respondents' agreement with the following statement: "Water rights are a private property right." We expect that farmers who agree or strongly agree with this statement are less likely to support larger reductions in water use than those who disagree because agreement may reflect a personal opinion that LEMA allocations are a type of takings of existing water rights. While a recent court ruling supports the legal authority of a LEMA, there are likely some farmers that disagree with the court ruling.

3.4.3 Econometric Model of Preferred Method of Assigning Allocations

In this section, we develop a model to analyze the preferences of farmers for the methods to use when calculating the allocated quantity of water use for each water right. The responses to the ranking of three consolidated methods shown previously in Table 3.1 provide the data for this analysis.

The most commonly used models for rank-order data are the multinomial logit model (McFadden, 1974) and the rank-ordered logit (ROL) model (Beggs and Cardell, 1981). Since the ROL considers the full ranking of the alternatives which contains more information than only the most preferred choice, it provides more efficient parameters estimates than the multinomial logit model. However, previous studies have raised concerns about the use of the ROL because they have shown that individuals' responses at lower ranking levels are not reliable (Foster and Mourato, 2002; Hausman and Ruud, 1987). This finding implies that the coefficient estimates attenuate toward zero when more rank levels are used in the ROL model. More recently, Yan and Yoo (2014) show that the attenuation of parameter estimates at higher rank depth is specific to the ROL model. The ROL model assumes a type 1 extreme-value (EV) distribution for its utility error term which relies on the independence of irrelevant alternatives (IIA) property. The IIA property implies that the conditional probability that an alternative is chosen at each rank is independent of the probability that another alternative has already been chosen at the earlier rank. However, with ordered alternatives, one alternative is similar to those close to it and less similar to those further away, which is a violation of the IIA assumption.

As an alternative to the ROL model, we estimate a rank-ordered probit (ROP) model which assumes a normal distribution of the utility error (Train, 2009). The ROP model is a more flexible behavioral structure to deal with rank-ordered data than the ROL model since it relaxes the IIA assumption. The ROP accounts for the correlations between choices among rank levels by estimating covariances between the error terms for the alternatives which reduces the attenuation of coefficients (Nair et al., 2019). One reason for the continued use of ROL for ranked data is that ROP can be computationally difficult to estimate in the presence of many alternatives. The likelihood function of the ROP model entails the evaluation of an analytically-intractable integral. Thus, the ROP uses maximum simulated likelihood (MSL) techniques to approximate the integral which has no closed-form solution and the computational cost to ensure good estimates was previously prohibitive. However, the availability of new analytical and simulation methods makes the estimation of the ROP model no longer intractable (Bhat, 2011, 2018).

Equation 3.2 describes the ROP model to be estimated:

$$Pr(Method_i^j) = \Phi[\beta_0^j + \beta_1^j[(1-D_i)ST_i + D_iK] + \beta_2^j D_i(ST_i - K) + \gamma'^j H_i + \theta'^j F_i + \alpha^{j'} X_i], \quad (3.2)$$

where the Φ is assumed to be a normal cumulative distribution function. The dependent variable is the probability of ranking method j as the best method by farmer i with j = Historical, Inches and Water Right. All of the explanatory variables are the same as in equation 3.1.

3.4.4 Expected Sign of Coefficient in Model of Preferred Method of Assigning Allocations

In general, we expect that a method of allocation will receive greater support by a farmer if it results in a smaller reduction from historical pumping and it is perceived as fair. However, making hypotheses about the expected sign of the variables affecting the preferred method is more challenging. One expectation could be that larger farms might be less willing to support a reduction based on water right characteristics because larger farms likely have a more diverse set of water rights and will have some that are harmed significantly more than others. We also expect that senior water rights will prefer the method that assigns allocations based on the water right. However, we have no a priori expectation on the sign of other variables included in the model.

3.5 Results

3.5.1 Evaluating the Preferred Reduction in Water Use

Table 3.4 shows the interval regression estimates for the preferred reduction in water use through the establishment of a LEMA. Column 1, shows the regression results when all of the variables capturing the aquifer characteristics are included in the model. The results show that a decrease in saturated thickness of 1 ft increases the average preferred water reduction by 0.22 percentage points when saturated thickness is lower than 70 ft. By contrast, when the level of saturated thickness is greater than 70 ft, a 1 ft decrease in saturated thickness has no significant impact on preferences. We also find that an increase in depth to water of 1 ft, increases the average preferred water reduction by 0.024 percentage points. However, we find no statistically significant impact of hydraulic conductivity or recharge on the preferences for reductions in water use.

Column 2, shows the results when we include the change in returns per acre of land that was initially irrigated as an explanatory variable instead of saturated thickness and depth to water. The coefficient on the change in returns to land that was initially irrigated indicates that a decrease in returns to land of $1 per acre increases the average preferred water reduction by 0.11 percentage points.

Table 3.4: Interval Regression Estimates for Preferred Reduction in Water Use

	(1)	(2)
$[(1-D_{it})ST_{it}+D_{it}K]$	-0.224***	
	(0.067)	
$D_{it}(ST_{it}-K)$	-0.004	
	(0.013)	
Change in saturated thickness	0.003	
	(0.080)	
Depth to water	0.024*	
	(0.013)	
Change in returns to land		-0.110**
		(0.050)
Hydraulic conductivity	0.020	0.033
	(0.026)	(0.029)
Natural Recharge	-0.350	-0.081
	(0.396)	(0.460)
Historical intensity of irrigation	-0.469	-0.489
	(0.292)	(0.321)
Density of wells	0.128*	0.070
	(0.066)	(0.059)
Proportion of farm irrigated	-5.508**	-5.843**
	(2.154)	(2.331)
Total cropland	-0.102	-0.117
	(0.108)	(0.114)
Average water right number	0.169	-2.246
	(4.326)	(4.517)
Crop Productivity Index	2.677	-0.960
	(6.333)	(6.756)
Proportion of acres owner-operator	6.442***	6.698**
	(2.386)	(2.693)
Proportion of acres tenant	1.795	2.584
	(2.493)	(2.851)
Proportion of acres local landlord	3.326	3.913
	(2.367)	(2.677)
Expect younger family to farm	-1.813	-1.509
	(1.305)	(1.407)
Proportion of income from farming	1.879	2.114
	(2.069)	(2.240)
Farmer age	0.024	0.030
	(0.047)	(0.053)
High education level	0.959	1.448
	(1.224)	(1.318)
Water rights private property: Agree	-3.719**	-3.716**
	(1.526)	(1.653)
Water rights private property: Strongly Agree	-8.721***	-8.725***
	(1.423)	(1.549)
N	402	372

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The coefficient estimates for other explanatory variables are similar for the two models presented in columns 1 and 2. Thus, we describe the results in column 1. Across all of the variables capturing characteristics of the water rights and farm, we find that only coefficients on the density of wells and the proportion of the farm that is irrigated are significant. Results show that an additional well in a radius of 2 miles increases the average preferred water reduction by 0.13 percentage points. We also find that an increase in the proportion of the farm irrigated by 0.1 decreases the preferred water reduction by 0.55 percentage points.

Lastly, we describe the coefficient estimates for the variables capturing farmers' characteristics. We find that an owner-operator prefers a 6.44 percentage point larger reduction in water use than a non-local landlord. Results also highlight the role of ideological differences among farmers in determining the preferences for reductions in water use. Farmers who agree or strongly agree that water rights are a private property right prefer about 3.72 and 8.72 percentage point smaller reductions in water use than those who disagree with the statement. We estimate equation 3.1 including all the explanatory variables except for this variable capturing differences in beliefs and we find similar results which reduces concerns that including this variable could give rise to misleading results due to multicollinearity with other variables.

To analyze what explanatory variables matter the most to explain the preferred reduction in water use we estimate a model with standardized variables. Since our model involves variables in different units of measurement, it is not possible to compare the relative importance of each coefficient using the regression results shown in Table 3.4. Each explanatory variable is standardized by subtracting the mean from each and then dividing by the standard deviation. Thus, standardized coefficients reflect the impact of a one standard deviation change in the variable and are useful for comparing the relative importance of the different explanatory variables on the preferred reduction in water use.

As column 1 in Table 3.5 shows, the explanatory variables that are most important to explain the preferred reduction in water use are: whether farmers strongly agree that water rights are a private property right, saturated thickness lower than 70 ft and the proportion of acres under owner-operator role. The alternative model specification in column 2, shows similar results but the second most important variable is the proportion of acres under owner-operator role followed by the change in returns to land that was initially irrigated.

Table 3.5: Standardized Interval Regression Estimates Preferred Reduction in Water Use

	(1)	(2)
$[(1 - D_{it})ST_{it} + D_{it}K]$	-3.025***	
	(0.909)	
$D_{it}(ST_{it} - K)$	-0.234	
	(0.829)	
Change in saturated thickness	0.045	
	(1.035)	
Depth to water	1.290*	
	(0.725)	
Change in returns to land		-2.058**
		(0.944)
Hydraulic conductivity	0.508	0.820
	(0.639)	(0.719)
Natural Recharge	-0.577	-0.134
	(0.652)	(0.758)
Historical intensity of irrigation	-1.170	-1.222
	(0.729)	(0.801)
Density of wells	1.576*	0.856
	(0.811)	(0.731)
Proportion of farm irrigated	-1.718**	-1.823**
	(0.672)	(0.727)
Total cropland	-0.554	-0.637
	(0.591)	(0.620)
Average water right number	0.027	-0.353
	(0.681)	(0.711)
Crop Productivity Index	0.266	-0.095
	(0.629)	(0.671)
Proportion of acres owner-operator	2.795***	2.906**
	(1.035)	(1.168)
Proportion of acres tenant	0.683	0.983
	(0.948)	(1.085)
Proportion of acres local landlord	1.316	1.548
	(0.936)	(1.059)
Expect younger family to farm	-0.895	-0.745
	(0.644)	(0.695)
Proportion of income from farming	0.624	0.702
	(0.687)	(0.744)
Farmer age	0.338	0.412
	(0.660)	(0.734)
High education level	0.480	0.725
	(0.612)	(0.659)
Water rights private property: Agree	-1.717**	-1.716**
	(0.705)	(0.763)
Water rights private property: Strongly Agree	-4.268***	-4.270***
	(0.696)	(0.758)
N	402	372

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We further explore which group of variables, either the characteristics of the aquifer or the characteristics of the farms and wells or the characteristics of the farmers, are the most important to explain the preferred reduction in water use. The partial R^2 is useful to answer this question if a OLS regression is implemented but is not possible to estimate with an interval regression. Therefore, we follow an alternative method where for each group of variables we use the estimates from the interval regression model to predict the preferred reduction in water use setting all of the variables except the ones included in the group equal to their mean. Then, we estimate the standard deviation of the prediction which reflects the variation predicted by each group of variables.

The results show that the individual characteristics are the most important variables to explain the variation of the preferred reduction in water use ($SD = 4.16$), followed by the characteristics of the aquifer ($SD = 3.31$) and the characteristics of the water rights and farms ($SD = 2.47$).

3.5.2 Evaluating the Preferred Method of Assigning Allocations

This section provides results for the analysis of the preferred method of assigning water allocations for each water right if the LEMA were implemented. The coefficient estimates for the ROP model can be difficult to interpret because of the normalization for location and scale. Thus, Table 3.6 shows the average marginal effects of the ROP regression. In general, the results indicate little effects of aquifer characteristics on the preferred method of allocations. A decrease in saturated thickness of 1 ft increases the probability of ranking the method “Water Right” as first on average by 0.0008 when saturated thickness is greater than 70 feet.

Larger farms are more likely to rank the method “Historical” as first while they are less likely to select method “Water Right” as their most prefer option. For example, an additional 1,000 cropland acres increases the probability of ranking the method “Historical” as first on average by 0.007 and decreases the probability of ranking the method “Water Right” as first on average by 0.010. As expected, more senior water right holders are more likely to select

"Water Right" as the best method. As results show, the probability of ranking the method "Water Right" as first increases on average by 0.248 when the water right is senior compared with junior water rights.

Table 3.6: Average Marginal Effects of ROP Regression of Preferred Method of Assigning Allocations

Variables	Historical	Inches	Water Right
$[(1-D_{it})ST_{it}+D_{it}K]$	0.001	0.0003	-0.001
	(0.002)	(0.003)	(0.002)
$D_{it}(ST_{it}-K)$	0.0005	0.0003	-0.0008**
	(0.0005)	(0.0005)	(0.0004)
Change in saturated thickness	0.002	-0.001	-0.001
	(0.003)	(0.003)	(0.002)
Depth to water	-0.00001	0.0003	-0.0002
	(0.0005)	(0.0005)	(0.0004)
Hydraulic conductivity	0.001	-0.0001	-0.001
	(0.0009)	(0.001)	(0.0008)
Natural Recharge	-0.009	0.017	-0.008
	(0.014)	(0.016)	(0.012)
Historical intensity of irrigation	-0.013	0.017	-0.004
	(0.010)	(0.012)	(0.009)
Density of wells	-0.003	0.004	-0.002
	(0.002)	(0.003)	(0.002)
Proportion of farm irrigated	0.112	-0.064	-0.048
	(0.078)	(0.090)	(0.066)
Total cropland	0.007**	0.003	-0.010***
	(0.004)	(0.004)	(0.004)
Average water right number	-0.038	0.286	-0.248*
	(0.153)	(0.175)	(0.130)
Crop Productivity Index	-0.221	0.069	0.152
	(0.228)	(0.262)	(0.191)
Proportion of acres owner-operator	-0.070	0.040	0.030
	(0.083)	(0.096)	(0.071)
Proportion of acres tenant	0.049	-0.106	0.057
	(0.089)	(0.103)	(0.075)
Proportion of acres local landlord	0.075	-0.011	-0.065
	(0.080)	(0.093)	(0.068)
Expect younger family to farm	-0.028	0.025	0.004
	(0.047)	(0.054)	(0.039)
Proportion of income from farming	-0.098	0.222***	-0.124**
	(0.075)	(0.085)	(0.063)
Farmer age	0.003*	-0.003	-0.00002
	(0.0017)	(0.0020)	(0.0014)
High education level	-0.033	-0.053	0.085**
	(0.043)	(0.050)	(0.036)
Water rights private property: Agree	-0.036	-0.029	0.065*
	(0.059)	(0.064)	(0.040)
Water rights private property: Strongly Agree	-0.123**	-0.041	0.165***
	(0.053)	(0.060)	(0.040)

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

An increase of 0.1 in the proportion of income from farming increases the probability of ranking the method “Inches” as first on average by 0.022 while decreases the probability of ranking the method “Water Right” as the best alternative on average by 0.012. One year increase in the age of farmers increases the probability of ranking the method “Historical” as first on average by 0.003. The probability of a farmer ranking method “Water Right” as first increases by 0.085 when their highest level of education is a bachelor or graduate degree. As expected, farmers who agree or strongly agree with the statement “water rights are a private property” rank method “Water Right” higher. The probability of ranking the method “Water Right” as first increases on average by 0.065 when farmers agree compared with those who disagree. Similarly, when farmers strongly agree with the statement, the probability of ranking method “Water Right” as the best option increases on average by 0.165, while the probability of ranking method “Historical” as the best option decreases on average by 0.123.

We also estimate an alternative ROP model specification including the change in returns per acre of land that was initially irrigated as an explanatory variable instead of saturated thickness and depth to water. We obtain very similar results to our main specification and for sake of space the table with results is included in the Appendix, Table B.1. We find that the change in returns per acre of land that was initially irrigated due to a change in saturated thickness is statistically insignificant to explain the preferred method of allocation.

Next, we examine what explanatory variables matter the most to explain the preferred method of allocation. We find that the most important variables to explain the probability of ranking the method “Historical” as the first are whether farmers strongly agree that water rights are a private property, farmer’s age and the size of the farm captured by the total cropland area. Similarly, the most important variables to explain the probability of ranking the method “Water Right” as the best method are whether farmers strongly agree that water rights are a private property, the size of the farm captured by the total cropland area and saturated thickness when it is initially greater than 70 ft.

Table 3.7: Standardized Average Marginal Effects of ROP Regression of Preferred Method of Assigning Allocations

Variables	Historical	Inches	Water Right
$[(1 - D_{it})ST_{it} + D_{it}K]$	0.015	0.0036	-0.019
	(0.032)	(0.037)	(0.026)
$D_{it}(ST_{it} - K)$	0.032	0.017	-0.049**
	(0.030)	(0.034)	(0.025)
Change in saturated thickness	0.029	-0.014	-0.015
	(0.037)	(0.042)	(0.031)
Depth to water	-0.0006	0.014	-0.013
	(0.026)	(0.030)	(0.021)
Hydraulic conductivity	0.024	-0.0028	-0.021
	(0.023)	(0.026)	(0.019)
Natural Recharge	-0.015	0.027	-0.013
	(0.023)	(0.027)	(0.020)
Historical intensity of irrigation	-0.033	0.042	-0.01
	(0.026)	(0.030)	(0.021)
Density of wells	-0.032	0.054	-0.021
	(0.029)	(0.033)	(0.024)
Proportion of farm irrigated	0.035	-0.020	-0.015
	(0.024)	(0.028)	(0.021)
Total cropland	0.040**	0.017	-0.057***
	(0.020)	(0.023)	(0.021)
Average water right number	-0.006	0.045	-0.039*
	(0.024)	(0.028)	(0.020)
Crop Productivity Index	-0.022	0.007	0.015
	(0.023)	(0.026)	(0.019)
Proportion of acres owner-operator	-0.030	0.017	0.013
	(0.036)	(0.042)	(0.031)
Proportion of acres tenant	0.019	-0.040	0.022
	(0.033)	(0.039)	(0.029)
Proportion of acres local landlord	0.030	-0.004	-0.026
	(0.032)	(0.037)	(0.027)
Expect younger family to farm	-0.014	0.012	0.0017
	(0.023)	(0.027)	(0.019)
Proportion of income from farming	-0.032	0.074***	-0.041**
	(0.025)	(0.028)	(0.021)
Farmer age	0.041*	-0.040	-0.0002
	(0.024)	(0.038)	(0.020)
High education level	-0.016	-0.026	0.042**
	(0.021)	(0.025)	(0.018)
Water rights private property: Agree	-0.018	-0.017	0.035
	(0.025)	(0.029)	(0.021)
Water rights private property: Strongly Agree	-0.061**	-0.021	0.082***
	(0.025)	(0.029)	(0.021)

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.6 Discussion

In general, we observe that as the aquifer is more depleted farmers support larger reductions in water use. These results are consistent with previous studies on collective action and benefits from management showing that collective action among water users is difficult unless they perceive that the aquifer is moderately depleted (e.g., Araral, 2009; Bardhan, 1993). Intuitively, farmers may have little incentive to support groundwater management when the resource is abundant. Specifically, we find that when initial saturated thickness is lower than 70 feet, the preferred reduction in water use is larger for smaller amounts of saturated thickness. However, when saturated thickness is greater than 70 feet, there is no impact of saturated thickness on the preferred reduction in water use. This result aligns with simulations conducted by Foster et al. (2017) that show areas with too large of a saturated thickness have smaller gains from pumping restrictions because the negative impacts of depletion are not imminent. Similarly, we find that as the returns to land are more negatively impacted by changes in saturated thickness, farmers prefer larger reductions in water use.

Edwards (2016) shows that counties with greater hydraulic conductivity and lower recharge benefit most after groundwater management is implemented relative to other counties. However, we find no significant impact of hydraulic conductivity or recharge on the preferred reduction in water use.

We show that some characteristics of water rights and the farm explain the preferred reduction in water use. The density of wells reflects how shared the aquifer is in a given location. For example, Pfeiffer and Lin (2012) find evidence of spatial externalities between neighboring groundwater users that result in increased groundwater extraction. Our results show some evidence that the density of wells might have an impact on the preferred reduction in water. Thus, these findings support our expectation that benefits from management increase with well density as the marginal externality imposed on neighboring wells decreases with distance. Furthermore, we show that as farmers irrigate a larger proportion of their land, they are less likely to support a large reduction in water use. This result may indicate that farmers that are more dependent on the aquifer tend to avoid short run declines in benefits from a restriction on water use.

Moreover, our results highlight the role of individuals characteristics in determining the preferences for reductions in water use. For example, owner-operator farmers are more likely to support larger reductions in water use than absentee landlords. As we expected, owner-operator farmers may be on average more forward-looking and more careful of their own resources than landlords. Furthermore, we find that differences in the preferences for water reduction are also explained by ideological differences among farmers. Farmers who strongly believe that water rights are a private property tend to support smaller reductions in water use. This result is consistent with a recent study by Perez-Quesada and Hendricks (2021) which concludes that ideological differences among farmers are likely to explain water users support to management plans.

When we consider the relative importance of each variable, we find that the most important variables determining the preferred reductions in water use are whether farmers strongly agree that water rights are a private property, the saturated thickness and the proportion of land under owner-operator role. Alternatively, when we consider the relative importance of different set of variables, we find that the set of variables reflecting individuals' characteristics explains most of the variation in the preferred water reductions.

These findings provide useful policy insight to better understand under what conditions local groundwater management is most likely to succeed. First, farmers located in areas where the aquifer is more depleted are more likely to support reductions in groundwater use through the establishment of a LEMA. Second, even though the depletion of the aquifer plays an important role explaining differences in the preferred reductions in water use, ignoring the effect of characteristics of the users can hinder collective action efforts. For example, to garner more support to establish a LEMA, groundwater managers might need to devote special attention to farmers who strongly agree that water rights are a private property, landlords and those who irrigate a larger proportion of their farm as opposition to reductions in water use are strongest among them.

The method of assigning allocations has a significant impact on the distribution of benefits and costs and can be a key impediment to obtain support among users. For example, Perez-

Quesada and Hendricks (2021) argue that the definition of individual groundwater allocations is a central issue in the LEMA negotiations. The methods that assign water allocations for each water right in the area where the LEMA is implemented should be considered fair by farmers and consider local conditions to garner more support among them (Ostrom, 2002).

We find no clear evidence of what are the main factors determining the preferred method of assigning water allocations which can make it difficult for local groundwater managers to identify which method is more likely to be considered fair by farmers. In general, the results indicate little effects of aquifer characteristics on the preferred method of allocations. Thus, it might be challenging for groundwater managers to identify, for example, which method is the most preferred where the aquifer is more depleted. Among all the characteristics of the water rights and the farm, only the size of the farm affects the preferred allocation method. Our results suggest that larger farms are more likely to rank the method “Historical” as first. Contrary, as the farm size increase, they are less likely to rank the method “Water Right” as the best option. This finding is consistent with our expectation that larger farms might be less willing to support a reduction based on water right characteristics because they likely have a more diverse set of water rights and will have some that are harmed significantly more than others.

As expected, farmers who strongly agree that water rights are a private property are more likely to rank the method “Water Right” as first, whereas they are less likely to rank the method “Historical” as the best option. We also find evidence that more educated farmers with a smaller proportion of their income coming from farming are more likely to rank the method “Water Right” as the best. In contrast, those whose income is obtained mostly from farming are more likely to select “Inches” as the most preferred method.

3.7 Conclusion

This study uses unique data obtained from consequential stated preferences surveys in the Kansas portion of the High Plains Aquifer to evaluate the factors that influence farmers preferred reductions in groundwater use through a localized and collaborative water conservation program.

Results indicate that farmers located in areas where the aquifer is more depleted are more likely to support larger reductions in groundwater use through the establishment of a LEMA. But we also find that ignoring the effect of characteristics of the users can prevent collective action efforts. Farmers who strongly agree that water rights are a private property, landlords and those who irrigate a larger proportion of their farm are less supportive for reductions in water use. Therefore, local groundwater managers might need to devote special attention to these types of farmers to garner more support to establish a LEMA. Further, the article analyzes farmers' preferences for the methods of assigning water allocations for each water right. We find that none of the methods are preferred by a majority of users and there is no clear evidence of what are the main factors determining the preferred method of assigning water allocations which can make it difficult for groundwater managers to identify which method is more likely to be considered fair by farmers.

The results of this article inform groundwater managers about the alternative factors they should consider to garner support among local water users for the implementation of a LEMA. This is relevant and insightful to managers of water throughout Kansas, the High Plains and other regions where conserving water resources is a high priority and localized and stakeholder-driven conservation plans could be a solution.

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Appendix A

Appendix to Chapter 2

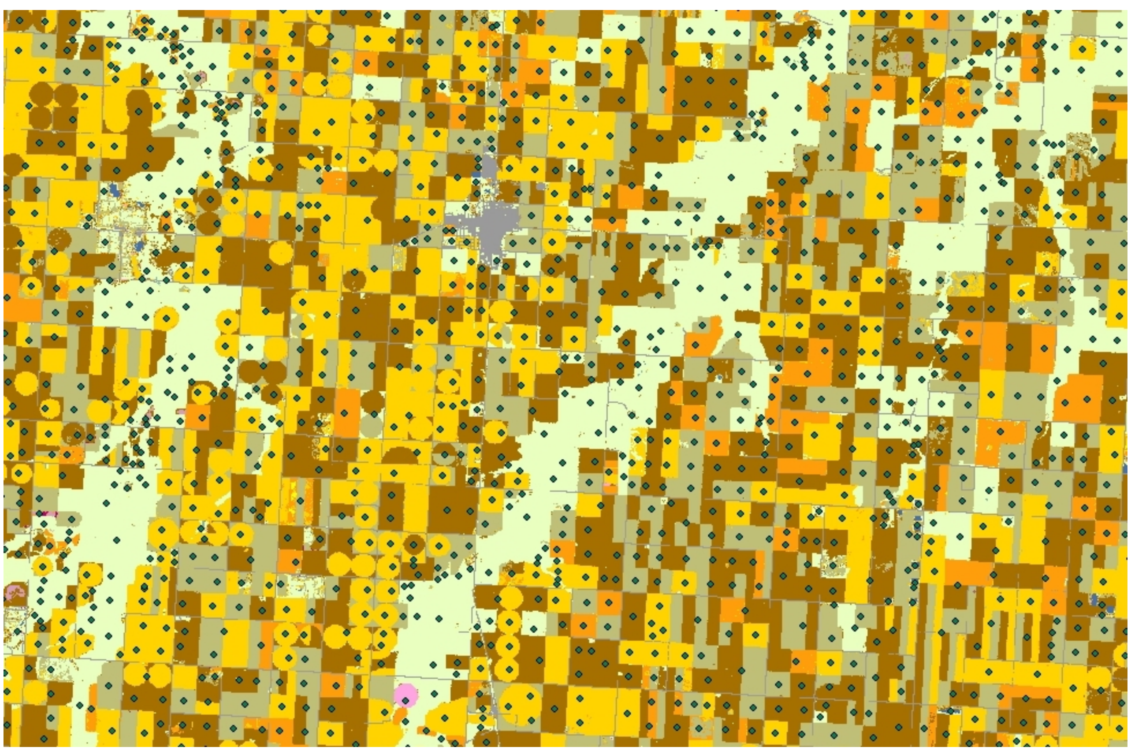

Figure A.1: Example of Cropland Data Layer with the points used as the unit of analysis for the econometric model.

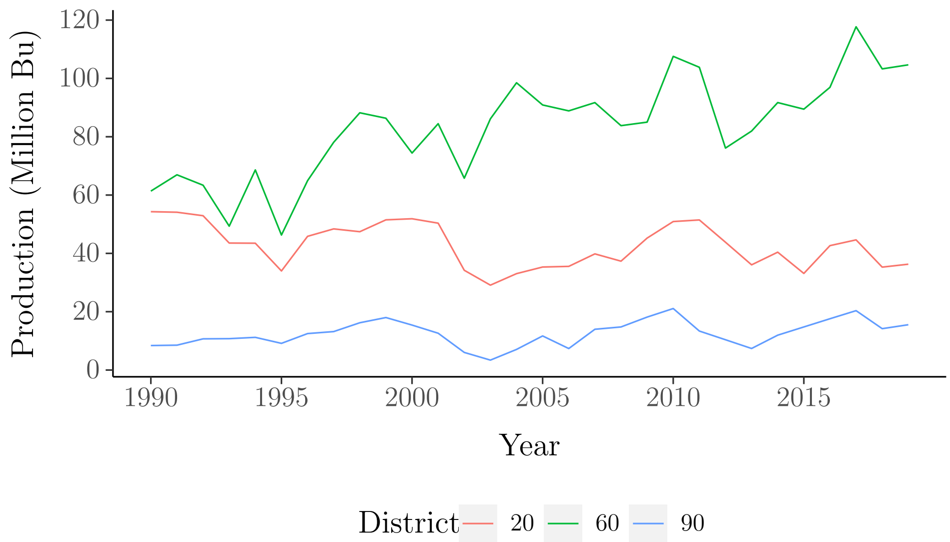

Figure A.2: Corn Production by Agricultural District in Colorado (1990-2019)

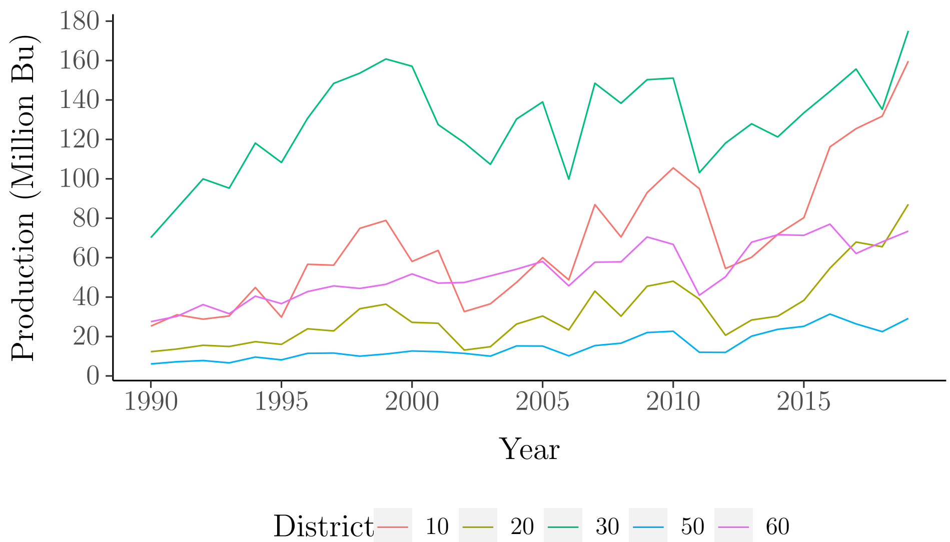

Figure A.3: Corn Production by Agricultural District in Kansas (1990-2019)

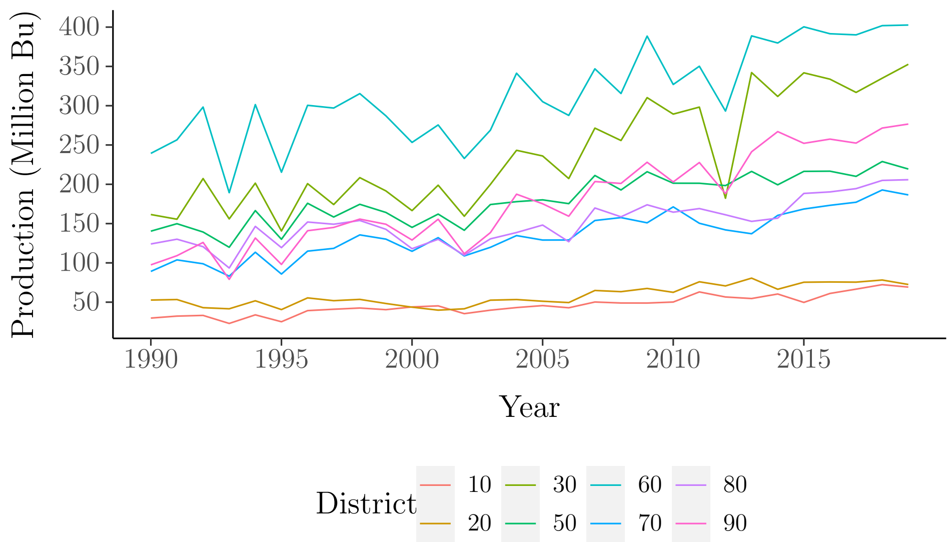

Figure A.4: Corn Production by Agricultural District in Nebraska (1990-2019)

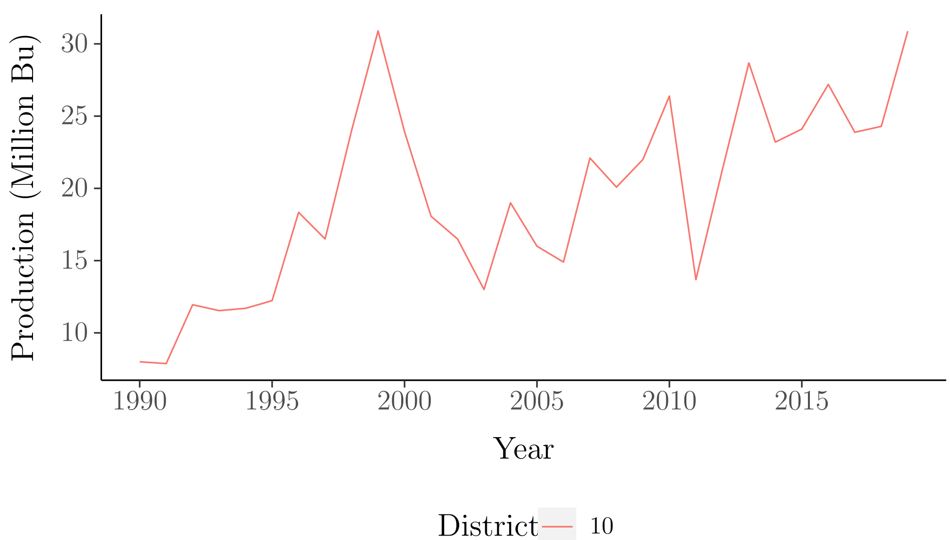

Figure A.5: Corn Production by Agricultural District in Oklahoma (1990-2019)

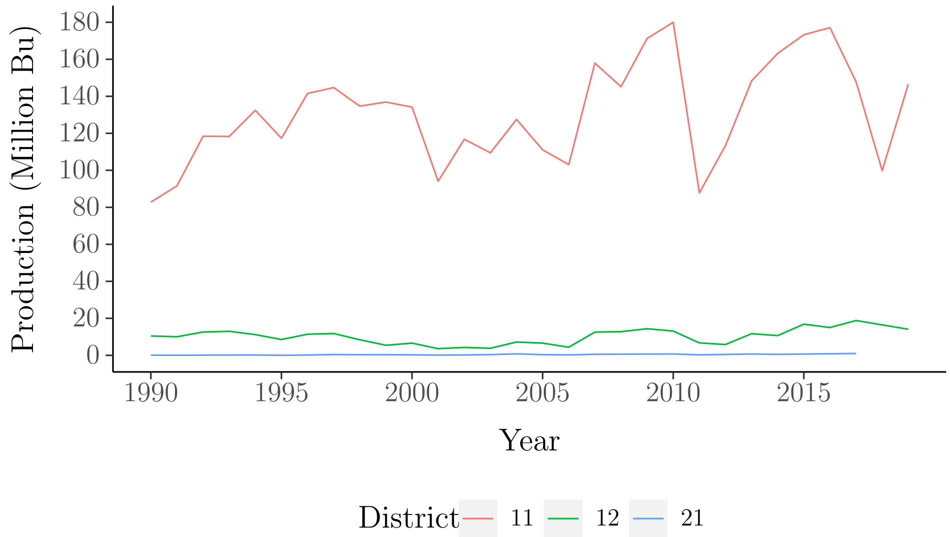

Figure A.6: Corn Production by Agricultural District in Texas (1990-2019)

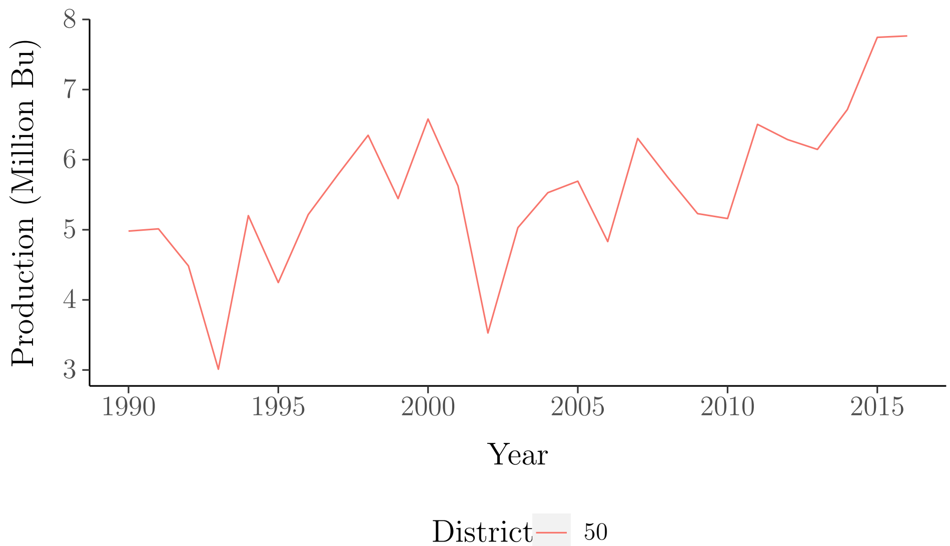

Figure A.7: Corn Production by Agricultural District in Wyoming (1990-2019)

Appendix B

Appendix to Chapter 3

Table B.1: Average Marginal Effects of ROP Regression of Preferred Method of Assigning Allocations

Variables	Methods Historical	Inches	Water Right
Change in returns to land	0.0003	0.0009	-0.0012
	(0.0017)	(0.0020)	(0.0014)
Hydraulic conductivity	0.001	-0.001	-0.0003
	(0.0010)	(0.0011)	(0.0008)
Natural Recharge	-0.013	0.021	-0.007
	(0.015)	(0.018)	(0.013)
Historical intensity of irrigation	-0.016	0.023*	-0.007
	(0.011)	(0.013)	(0.009)
Density of wells	-0.002	0.003	-0.0007
	(0.0020)	(0.0023)	(0.0017)
Proportion of farm irrigated	0.086	-0.017	-0.069
	(0.079)	(0.093)	(0.068)
Total cropland	0.008**	0.0023	-0.011***
	(0.0038)	(0.0043)	(0.0040)
Average water right number	0.072	0.222	-0.294**
	(0.150)	(0.177)	(0.134)
Crop Productivity Index	-0.212	-0.076	0.288
	(0.223)	(0.265)	(0.193)
Proportion of acres owner-operator	-0.101	0.038	0.066
	(0.086)	(0.102)	(0.075)
Proportion of acres tenant	-0.013	-0.053	0.066
	(0.093)	(0.110)	(0.081)
Proportion of acres local landlord	-0.017	0.054	-0.037
	(0.084)	(0.099)	(0.074)
Expect younger family to farm	-0.057	0.052	0.005
	(0.047)	(0.056)	(0.041)
Proportion of income from farming	-0.096	0.207**	-0.111*
	(0.077)	(0.089)	(0.066)
Farmer age	0.003	-0.003	-0.0005
	(0.0018)	(0.0021)	(0.0015)
High education level	-0.028	-0.074	0.102***
	(0.044)	(0.052)	(0.038)
Water rights private property: Agree	-0.035	-0.014	0.048
	(0.060)	(0.068)	(0.042)
Water rights private property: Strongly Agree	-0.104*	-0.051	0.155***
	(0.054)	(0.063)	(0.043)

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Standardized Average Marginal Effects of ROP Regression of Preferred Method of Assigning Allocations

Variables	Historical	Inches	Water Right
Change in returns to land	0.005	0.017	-0.022
	(0.031)	(0.037)	(0.027)
Hydraulic conductivity	0.033	-0.026	-0.007
	(0.024)	(0.027)	(0.029)
Natural Recharge	-0.022	0.034	-0.012
	(0.025)	(0.030)	(0.022)
Historical intensity of irrigation	-0.039	0.057*	-0.018
	(0.026)	(0.032)	(0.023)
Density of wells	-0.030	0.038	-0.008
	(0.025)	(0.029)	(0.021)
Proportion of farm irrigated	0.027	-0.005	-0.022
	(0.024)	(0.029)	(0.022)
Total cropland	0.046**	0.013	-0.058***
	(0.021)	(0.023)	(0.022)
Average water right number	0.011	0.035	-0.046**
	(0.024)	(0.028)	(0.021)
Crop Productivity Index	-0.021	-0.007	0.029
	(0.022)	(0.026)	(0.019)
Proportion of acres owner-operator	-0.044	0.016	0.028
	(0.037)	(0.044)	(0.033)
Proportion of acres tenant	-0.005	-0.020	0.025
	(0.035)	(0.042)	(0.031)
Proportion of acres local landlord	-0.007	0.021	-0.015
	(0.033)	(0.039)	(0.029)
Expect younger family to farm	-0.028	0.026	0.002
	(0.023)	(0.028)	(0.020)
Proportion of income from farming	-0.032	0.069**	-0.037*
	(0.025)	(0.030)	(0.022)
Farmer age	0.036*	-0.042	-0.006
	(0.025)	(0.030)	(0.021)
High education level	-0.014	-0.037	0.050***
	(0.022)	(0.026)	(0.019)
Water rights private property: Agree	-0.017	-0.009	0.026
	(0.026)	(0.031)	(0.023)
Water rights private property: Strongly Agree	-0.051**	-0.026	0.076***
	(0.026)	(0.031)	(0.022)

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.