

Fixed Effects Estimation of the Intensive and Extensive Margins of Irrigation Water Demand

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Irrigation water demand is estimated using field-level panel data from Kansas over 16 years. The cost of pumping varies over time due to changes in energy prices and across space due to differences in the depth to water. Exploiting this variation allows us to estimate the demand elasticity while controlling for field-farmer and year fixed effects. Fixed effects also allow us to control for land use without an instrument or assumptions about the distribution of errors. Our estimates of water demand are used to calculate the cost of reducing irrigation water use through water pricing, irrigation cessation, and intensity-reduction programs.

Key words: fixed effects, High Plains Aquifer, water demand

Introduction

Growing pressures on water supplies from population growth, ecological needs, and climate stress have prompted renewed focus on irrigated agriculture, the largest water consumer in many arid regions. A critical parameter in determining the impacts of changes in water-related policies or markets is the own-price elasticity of irrigation water demand. For example, highly inelastic demand implies that water pricing policies would need to impose dramatically larger prices on irrigators to obtain even a modest reduction in water use, leading to large losses in producer surplus. Similarly, if demand is inelastic, then exogenous market changes such as increased energy prices—which raises the cost of the energy-intensive water delivery process—will have small effects on total water use but generate more noticeable impacts on farmers' welfare.

Although the importance of the elasticity parameter is recognized in the literature (e.g., see Olmstead, 2010), few general statements can be made about policy or market impacts because empirical elasticity estimates vary widely. In a meta-analysis of 24 water demand studies, estimates of the elasticity ranged from -0.001 to -1.97, with a mean of -0.48 and a standard deviation of 0.53 (Scheierling, Loomis, and Young, 2006). Few studies have employed microdata; two notable exceptions are a study by Moore, Gollehon, and Carey (1994), who used farm-level data on crop choices and crop-level irrigation deliveries spanning two time periods, and another by Schoengold, Sunding, and Moreno (2006), who estimated water demand from a 7-year panel of water- and land-use observations at the square-mile level.

We estimate irrigation water demand using a 16-year panel dataset encompassing over 14,000 individual fields overlying the Kansas portion of the High Plains Aquifer. Groundwater irrigators in Kansas do not pay for the water they pump but do incur a cost from the energy used to extract the water. This extraction cost can be reliably computed from well-known engineering formulas and

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varies both cross-sectionally due to heterogeneous pumping depths and temporally due to fluctuating energy prices during the sample period. Furthermore, when energy prices increase, the cost of extraction increases more in areas that have a greater depth to water. This source of variation allows us to identify the marginal effect of water price while controlling for field-farmer and year fixed effects.

Although a fixed-effects model does not allow us to identify the effects of variables that are constant over time or across fields, it is well-suited to our estimation objective of isolating the impact of water price. Using only cross-sectional or time series variation in the cost of pumping is problematic. Locations that have a greater depth to water, and thus a larger cost of pumping, may also have soil attributes that are correlated with water demand such that cross-sectional estimates of water demand are biased. In recent years, energy prices have been highly correlated with crop prices, making it difficult to identify demand from purely time-series variation in natural gas prices.¹

Nataraj and Hanemann (2011) recognize analogous difficulties in estimating urban water demand. They exploit a change in the pricing structure from a policy that only affected high-use households. Then they regress water use on the “treatment” indicator while controlling for year and household fixed effects to obtain a difference-in-differences estimate of the demand elasticity. In this article, we exploit the two-dimensional variation in the cost of pumping while controlling for fixed effects to estimate irrigation water demand. We find that irrigation water demand is highly inelastic in Kansas, with a demand elasticity of -0.10 . The value of irrigation water implied by our demand estimates is consistent with the difference in irrigated and nonirrigated cash rents in Kansas, giving us confidence in our estimates.

We also decompose the elasticity into extensive and intensive margin effects in the spirit of Moore, Gollehon, and Carey (1994) and Schoengold, Sunding, and Moreno (2006). If most of the response is at the intensive margin, then policies that target per-acre irrigation rates will be nearly as cost-effective as a first-best pricing policy. In addition, the induced impacts of the demand response on land use and the agricultural output mix are of interest as such changes are linked to other environmental indicators such as nonpoint source water pollution, carbon sequestration, and bioinvasions.

To decompose the elasticity we include binary land use variables in our water demand regression. Land use is likely correlated with unobserved variables affecting water use. Previous literature has often used methods proposed by Dubin and McFadden (1984) to correct for this bias either by using instrumental variables or imposing assumptions about the distribution of errors. In contrast, it is argued that fixed effects eliminate this bias by controlling for time-invariant unobserved heterogeneity.

We apply our demand estimates to calculate the cost of obtaining a given reduction in agricultural water use from three classes of commonly discussed water management policies: water pricing, irrigation cessation (variations of “water right buyout” programs), and reductions in per-acre irrigation rates. A straightforward implication of the declining marginal productivity of water is that irrigation cessation programs, which reduce irrigation to zero on the selected parcels, will be more costly in welfare terms than water pricing, which induces a smaller reduction on all parcels in a way that equates their marginal value products. However, we are aware of no empirical estimates of the additional costs of cessation, which is an important question given the increasing popularity of such programs. Our estimates imply that at an annual cost of \$3.45 million, the state of Kansas could reduce water use by about 2.17% with a water-right buyout program, in which each seller of a water right is compensated for his lost producer surplus from irrigation. If the state invested an equivalent amount to make lump-sum transfers to compensate all irrigators for their lost surplus from a pricing program, water use could be reduced by 15%, a nearly 7 fold-improvement in cost-effectiveness.

¹ In the second half of our data period, 2000-2007, expected prices of corn, soybeans, and wheat had correlation coefficients of 0.56, 0.82, and 0.81 with the price of natural gas. Expected prices of these crops are defined as the price of a harvest time futures contract prior to planting. For a discussion on the link between energy and non-energy commodity prices see Baffes (2009).

Table 1: Descriptive Statistics

Variable	Mean	Overall <i>Std.Dev.</i>	Between <i>Std.Dev.</i>	Within <i>Std.Dev.</i>
Applied Water per Acre (inches)	13.80	5.94	4.95	4.16
Area Irrigated (acres)	136.51	39.92	39.07	13.97
Pumping Cost (\$/acre-inch)	0.80	0.70	0.70	0.35
Jan-April Precip (inches)	4.31	2.31	1.53	1.94
May-Aug Precip (inches)	12.37	6.57	3.88	6.06
May-Aug ET (inches)	35.14	5.22	3.64	4.44
Proportion Corn	0.50	0.46	0.35	0.34
Proportion Soybeans	0.11	0.28	0.17	0.24
Proportion Alfalfa	0.10	0.30	0.27	0.17
Proportion Wheat	0.09	0.24	0.19	0.18
Proportion Sorghum	0.04	0.17	0.13	0.14
Proportion Other	0.02	0.13	0.09	0.11
Proportion Multiple	0.11	0.31	0.26	0.20
Proportion Double	0.02	0.15	0.10	0.13
Proportion Furrow	0.12	0.32	0.31	0.14
Proportion Standard CP	0.40	0.49	0.39	0.35
Proportion Low drops	0.48	0.50	0.40	0.36

We begin by describing the data and the features of irrigation in Kansas that drive our empirical specification. Next, the elasticity of water demand is decomposed into extensive, direct intensive, and indirect intensive margins. Then we explain the identification strategy for estimating the total demand elasticity and each of its components and present demand estimates. We argue in these sections that fixed effects regression removes any omitted variable bias and consistently estimates the parameters of interest. Finally, we describe the cost-effectiveness of the three policy classes noted above and use our estimates of irrigation water demand to calculate the cost of each policy.

Data

The data are from a 41-county region in western Kansas overlying the High Plains Aquifer. Our unbalanced panel spans 1992-2007 and includes 14,392 unique fields and 7,203 unique farmers. There are a total of 152,654 non-missing observations; several fields have missing observations in individual years. Descriptive statistics are provided in table 1.

Many of the variables in our dataset were taken from a unique database known as the Water Rights Information System (WRIS). By Kansas law, all water right holders are required to annually report their water use on each irrigated field, together with the crop grown, the area irrigated, and the type of irrigation delivery system.

The High Plains Aquifer is the source of water for about 98% of irrigated fields in Kansas. Return flows in our study region are negligible as the hydrology of the High Plains Aquifer makes it essentially a nonrenewable resource. The most appropriate measure of water conservation is, therefore, a reduction in applied water. While the WRIS system includes reports from surface water irrigators, we only consider groundwater irrigators in our sample.

The typical field with a center pivot is about 120-130 acres and fields with furrow irrigation are typically 80 or 160 acres. However, these are only typical and fields of every size are reported, especially for furrow irrigation. We only include fields between 60 and 275 acres in our sample. This includes most of the fields and prevents outliers from skewing our results.²

² Restricting field size in our sample reduced the number of observations by 24%.

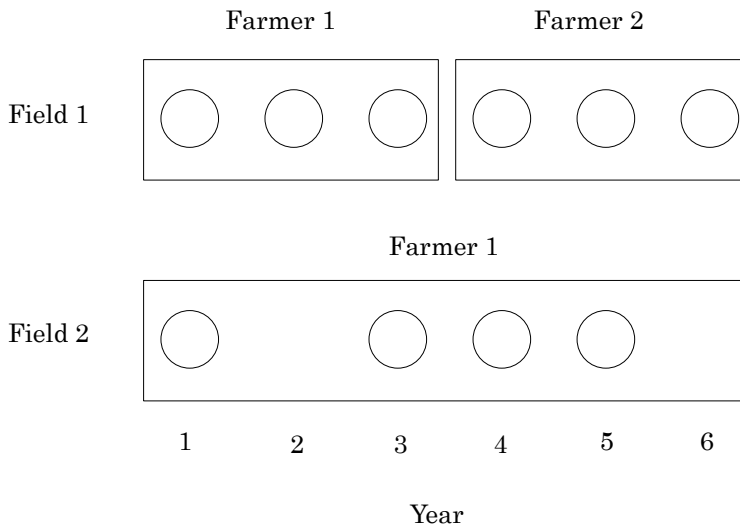


Figure 1: Visual Example of Data

The WRIS database also includes an identification number for each person who filed the water report, the individual we define as the “farmer.” In cases of rented land, either the landlord or the tenant may file the water report, but most likely it is the person with direct management over the field, since he or she would have knowledge about water applied and the crop grown.

To clarify the structure of our data, we provide a visual example of a set of observations in figure 1. We define a *field* as the land area authorized for irrigation from a single well. An *observation* in our dataset is defined as a unique field and year combination; different observations are represented as the circles in the diagram. Each rectangle in the figure is a *panel*, containing all observations from a unique field-farmer combination. In the example, field 1 changes management during the data period so its observations are divided into two panels. Farmer 1 operates two fields, but each is treated as a separate panel. The example also illustrates that a field may have missing data in particular years.

Our water price variable reflects the energy cost of extracting irrigation water, which represents approximately 10% of costs for growing corn in western Kansas, a slightly greater share of costs than land rent (Dumler et al., 2009). Unfortunately, the WRIS data do not contain information on the irrigator’s energy source or energy expenses. Natural gas price is used as the relevant energy price facing farmers. According to the 1998 Farm and Ranch Irrigation Survey (FRIS), natural gas, diesel fuel, and electricity were the energy source of 72.9%, 13.2%, and 11.1% of irrigated acres in Kansas, respectively. The 2003 FRIS showed a reduction in irrigators with natural gas wells while diesel and electricity wells increased. However, using energy price data from the Energy Information Administration (EIA), we found that natural gas and diesel prices are highly correlated (0.93) while natural gas and electricity prices are correlated to a lesser extent (0.73). The price of natural gas in our analysis is the average of the June and July industrial price for natural gas at the national level reported by EIA.³

Farmers’ water price is the cost of pumping an acre-inch of water to the surface, computed as (Rogers and Alam, 2006):

$$(1) \quad p = \phi p_g l,$$

³ The industrial price is the relevant price facing agricultural users. Data for the industrial price at the state level were only available beginning in 1997.

where p_g is the price of natural gas (\$/Mcf), l is pumping lift or depth to water (feet), and the constant $\phi = 0.00186$ is the amount of natural gas (Mcf) required to lift 1 acre-inch of water 1 foot.⁴ To calculate this cost for each observation, we obtained the depth to water in 2001 and the change in the depth to water from 1991 to 2001 from the Kansas Geological Survey's Section-Level Database. The Kansas Geological Survey constructed the Section-Level Database by interpolating values to each legal section from measurements at a smaller number of locations. This interpolation is convenient for creating maps of the aquifer, but may pose problems for quantitative analysis. As recommended by the Kansas Geological Survey, we merged the variables from the Section-Level Database to the WRIS data at the township level since we use the data for quantitative analysis.

As shown in table 1, calculated water price varies substantially in both cross sectional and temporal dimensions, with a between standard deviation of 0.7 and a within standard deviation of 0.348, relative to a mean of 0.8.⁵ Note that when the price of natural gas increases, the cost of pumping increases more in areas with a greater depth to water. Since we include both field-farmer and year fixed effects in the analysis, it is this source of variation in the cost of pumping that provides our identification.

Precipitation and evapotranspiration (ET) data are from the Kansas Weather Data Library and are spatially uniform within each agricultural statistics district. Weather observations for the northwest, west central, southwest, and south central districts were taken from the Colby, Tribune, Garden City, and St. John weather stations, respectively. ET is the amount of water lost into the air through both evaporation and transpiration, which depends on solar radiation, temperature, wind, and humidity. For this dataset, calculation of ET is alfalfa-based. Precipitation data at the district level are a proxy for the actual precipitation at each field. We argue in the results section that using a proxy for precipitation will not bias our estimate of the demand elasticity, but the coefficients on precipitation will have attenuation bias due to measurement error.

The most common irrigated crops grown in Kansas are corn, soybeans, alfalfa, wheat, and sorghum. "Other" crops include sunflowers, barley, oats, rye, and dry beans. About 32% of the observations reported that the field was split between crops. Unfortunately, the number of acres planted to each crop in these situations was not reported, nor was the water applied to each crop. We simply assume that if k crops were grown, the proportion of the field in each crop was $1/k$. In some cases it was only reported that "multiple" crops were grown, but not which crops were grown. There were also a few observations that double-cropped (i.e., grew two crops on the entire field in the same year).⁶

The most common irrigation systems are furrow, standard center pivot, and center pivot with low drop nozzles.⁷ Furrow irrigation, the least efficient of the three systems, uses gravity to deliver water to the crops through ditches in the field rows. Standard center pivot systems, which are of intermediate efficiency, deliver water above the crop canopy via pressurized sprinkler heads on a constructed boom that mechanically "pivots" around a center point in the field. The center pivot

⁴ The constant assumes the pump is operating at the full Nebraska Pumping Plant Criteria.

⁵ The calculated values p have a potential measurement error because we do not have data on the of depth to water at each location each year. We instead interpolated l for each observation from the Kansas Geological Survey's reported depth in 2001 and the reported change from 1991 to 2001 at each location. However, the interpolated portion of the pumping cost variable makes up a very small portion of the time series variation within panels, and in practice, the interpolated portion makes very little difference in our empirical estimates. The vast majority of the time series variation in the pumping cost is due to changes in the price of natural gas. The within standard deviation of the pumping cost is 0.348 if we incorporate the change in the depth to water over time and is 0.323 if we assumed a constant depth to water over time. Our elasticity estimates are virtually identical either way.

⁶ In their annual reports, farmers must indicate the crop grown by reporting a crop code. There are a large number of crop codes, where several of them refer to single crops, such as corn, wheat, etc. Several other codes refer to mixed cropping situations, e.g., "corn and wheat," where the field is divided and two crops are grown side by side. Yet another code is for "double-cropping," where two crops were grown on the same acreage during different periods of a single year. Lastly, farmers may report the code for "multiple" crops; in these cases it is not clear whether they grew a combination not on the code list or if they misunderstood the existing crop codes.

⁷ Subsurface drip irrigation was only reported for 0.4% of fields in 2007.

with low drop nozzle system is similar to the standard center pivot except that water is delivered below the crop canopy through nozzles at the bottom of drop tubes suspended from the boom. The low drop nozzle system is the most efficient of the three because less water is lost to evaporation during delivery.

Decomposition of the Elasticity of Water Demand

Consider a farmer's demand for irrigation water on a particular tract of land where p is the price of water. Let $a(p)$ denote the optimal irrigated acreage, let $w_j(p)$ denote the optimal water application per acre (acre-inches per acre) for each of the possible $j = 1, \dots, J$ land uses, and let $s_j(p)$ denote the optimal share of irrigated acreage planted to land use j . For this article we define "land use" as a crop and irrigation system pair. The average water applied per acre is $w(p) = \sum_{j=1}^J s_j(p)w_j(p)$.

Here we keep notation simple—for the purpose of decomposing the demand elasticity—by writing demand as only a function of the price of water. Water demand depends on several other factors such as crop prices, other input prices, farm programs, soil characteristics, and hydrologic characteristics. In the empirical model, we control for other prices and farm programs with year fixed effects and control for field and farmer heterogeneity with field-farmer fixed effects.

Water demand at the tract level can be written as:

$$(2) \quad q(p) = a(p)w(p),$$

where $q(p)$ denotes the total quantity of water demand. Differentiating equation (2) and multiplying by p/q reveals one decomposition of the water demand elasticity:

$$(3) \quad q'(p) \frac{p}{q} = a'(p) \frac{p}{a} + w'(p) \frac{p}{w}$$

$$\eta_q = \eta_a + \eta_w,$$

where primes denote first derivatives. We refer to η_a as a pure extensive margin effect, as it measures only the effect of an incremental expansion in irrigated acreage holding the s_j 's and w_j 's constant. Previous literature sometimes uses the term "extensive margin" effect to include changes in the mix of land uses as well as a possible expansion in irrigated area. In our case, changes in land use are embedded within η_w , which we define here as the total intensive margin effect. Estimates of η_a and η_w can be obtained by separately estimating the acreage demand function, $a(p)$, and the water intensity function, $w(p)$, and then computing the respective elasticities.

The total intensive margin effect can itself be decomposed. Differentiating $w(p) = \sum_j s_j(p)w_j(p)$ and multiplying by p/w gives:

$$(4) \quad \eta_w = \frac{p}{w} \left[\sum_{j=1}^J s_j(p)w_j'(p) + \sum_{j=1}^J s_j'(p)w_j(p) \right]$$

$$= \eta_{ww} + \eta_{ws},$$

where η_{ww} is the direct intensive margin effect and η_{ws} is the indirect intensive margin effect. The direct intensive margin effect is a change in water applied per acre through changes in the water applied on each land use (e.g., reducing water use on furrow irrigated corn). The indirect intensive margin effect is a change in water applied per acre through changing land uses, holding water application on the land use and total irrigated acres fixed (e.g., reducing water use by switching to a less water intensive crop).

Empirical Model

Intensive and Extensive Margins

To recover estimates of the extensive and intensive elasticities in equation (4), we separately estimated reduced form fixed-effects equations with irrigated acres, a_{it} , and applied water per acre, w_{it} , as the dependent variables for panel i in year t . The reduced form equation for w_{it} is:

$$(5) \quad w_{it} = \mathbf{X}'_{it}\beta_u + \alpha_i + \gamma_t + \varepsilon_{it},$$

where \mathbf{X}_{it} is a vector of the pumping cost and weather variables (precipitation and ET), β_u is a vector of parameters to be estimated, α_i captures the effect of field and farmer characteristics such as soil characteristics and management ability, γ_t captures the effect of macro-level shocks which affect all fields and farmers, such as changes in crop prices and farm programs, and ε_{it} is an idiosyncratic error term. The subscript u refers to “unconditional” parameters because they are not conditioned on land use. The unconditional model identifies the effect of a change in the cost of pumping on the water applied, allowing for any changes in land use that may occur as a result.

The equation for irrigated acreage is defined similarly to equation (5), except within-season weather variables are not included as explanatory variables because farmers make their acreage decision before these variables are known. The acreage equation captures farmers’ chosen adjustments to irrigated field size. Farmers with furrow irrigation can adjust irrigated acreage by varying the length of the gated pipe along the field edge, while center-pivot irrigators would alter the arc of coverage (for example, irrigate only half of the circle).

In both equations, the pumping cost variable was calculated from equation (1). The pumping cost is taken as exogenous to the farmer even though his withdrawals affect the depth to water and hence pumping costs in future periods. The assumption here is that farmers behave myopically, considering only current-period conditions when deciding the quantity to pump. Myopic behavior would hold strictly for large aquifers with instantaneous lateral flows; such resources are common pools so that each user obtains only a negligible private benefit in the future from restricting current pumping. The measured rate of lateral flow in the High Plains and similar aquifers is relatively slow, implying that an individual likely obtains some private benefit from reduced pumping (Beattie, 1981). Formally, an irrigator responds to an implicit price that is the sum of the current pumping cost and a user cost reflecting the effects on future pumping costs. However, the effect of user cost on pumping vanishes as the elasticity of demand approaches zero (Koundouri, 2004; Wang and Segarra, 2011). A number of numerical optimization studies have found only a small gap between the dynamic and myopic solutions in aquifers similar to the High Plains. Savage (2011) performed an econometric analysis of pumping data from the Nebraska portion of the High Plains aquifer and could not reject the hypothesis of myopic pumping.

Our estimate of the demand elasticity is a short-run effect, identifying farmers’ year-to-year changes in water use in response to yearly changes in energy prices. Given that the major crops in Kansas are annual crops, farmers can alter their crops in the short-run in addition to implementing management practices to reduce water use on a given crop.

Conceptually, the short-run response is smaller than the long-run response where irrigators can respond to price changes by adjusting irrigation capital. Scheierling, Loomis, and Young (2006), however, found that the difference in the elasticity estimates between long-run and short-run studies were not statistically significant. Here, we do not explicitly model the irrigation technology investment decision, which would require a multiperiod dynamic model with forward-looking measures of expected changes in prices and costs. To whatever extent irrigators interpret yearly changes in the energy price as an indicator of a long-term price shift, which then induces them to invest in new capital within the year, these responses are embedded within our elasticity estimate. In any case, the short-run elasticity is arguably the most policy-relevant measure in western Kansas

because there is relatively little remaining opportunity for substantial water conservation through the adoption of more efficient technologies.⁸

The panel-specific fixed effects, α_i , allow the most flexibility possible in capturing differences across fields and farmers. If the farmer associated with the field changes, then the new farmer-field combination has a new fixed effect, which removes any management bias. The fixed effects estimator we use is the within estimator which is equivalent to the least-squares dummy variable estimator where a binary variable is specified for each panel. We cluster the standard errors at the farmer level, allowing for any form of error correlation for a given farmer as well as heteroskedasticity across farmers.

Direct Intensive Margin

The direct intensive margin effect is the change in applied water per acre holding land use constant, which is estimated with the reduced form equation:

$$(6) \quad w_{it} = \mathbf{X}'_{it}\beta_c + \mathbf{D}'_{it}\delta + \alpha_i + \gamma_t + \varepsilon_{it},$$

where \mathbf{D}_{it} is a vector of binary variables indicating different land uses, and (δ, β_c) is the set of parameters to be estimated. For ease of notation, α_i , γ_t , and ε_{it} represent the fixed effects and residual as in equation (5), even though they will assume different values in this model. The subscript c refers to the parameters “conditional” on land use.

A potential complication in estimating equation (6) is that the land-use variables, \mathbf{D}_{it} , may be correlated with the error. This may be understood either as an endogeneity problem where land use is an endogenous variable, or as a sample selection problem where observed land use conditions the sample from which to estimate irrigation intensity. Intuitively, this problem arises because the same unobserved factors that drive land use choices may also influence water use. For example, if a farmer growing corn uses more water than a farmer growing wheat, this may not be sufficient evidence that corn is a more water intensive crop: there could be unobservable characteristics of the farmer and field where corn is grown that make corn a more likely choice and also lead to more water use (on all crops).

Following Dubin and McFadden (1984) and Lee (1983), previous studies on water, electricity, and gas demand have corrected for selection bias either by including an additional correction term in the regression (e.g., Moore, Gollehon, and Carey, 1994; West, 2004; Mansur, Mendelsohn, and Morrison, 2008) or using predicted probabilities as instruments (e.g., Mannering and Winston, 1985; Schoengold, Sunding, and Moreno, 2006). However, the use of a correction term requires assumptions about the distribution of errors in the discrete and continuous models. The Dubin and McFadden (1984) formulation also requires a particular structural representation. Using predicted probabilities as instruments does not require distributional assumptions, but only identifies the coefficient from the nonlinearity of the probabilities, unless an instrumental variable is available. In our application it is difficult to think of a variable that is correlated with land use but not correlated with water use.⁹

Fixed effects estimates correct for the selection bias without any instrumental variables or assumptions about distributions as long as \mathbf{X}_{it} and \mathbf{D}_{it} are strictly exogenous conditional on the unobserved effect; that is $E[\varepsilon_{it} | \mathbf{X}_{i1}, \dots, \mathbf{X}_{iT}, \mathbf{D}_{i1}, \dots, \mathbf{D}_{iT}, \alpha_i, \gamma_t] = 0$ for all it , or equivalently

⁸ By 2007, 96% of fields had adopted center pivot technology. We find that center pivot technology results in significant water conservation compared to furrow irrigation, but water use with the two types of center pivot irrigation are not significantly different. Drip irrigation, which is more efficient, is not likely to be rapidly adopted in the near future in Kansas as the most modern center pivot systems are nearly as efficient and the gain in yields from drip systems does not overcome their substantial investment costs (Peterson and Ding, 2005). As of 2007, only 0.4% of fields in our study region had adopted drip irrigation.

⁹ Lagged land use is correlated with field and farmer unobservables that affect water use. However, lagged land use does become a valid instrument after controlling for fixed effects.

(Wooldridge, 2002):

$$(7) \quad E[w_{it} | \mathbf{X}_{i1}, \dots, \mathbf{X}_{iT}, \mathbf{D}_{i1}, \dots, \mathbf{D}_{iT}, \alpha_i, \gamma_i] = \mathbf{X}'_{it} \beta_c + \mathbf{D}'_{it} \delta + \alpha_i + \gamma_i.$$

Conditional strict exogeneity assumes that current water use is unrelated to previous or future land use, conditional on α_i . Intuitively, we identify the difference in water use by different crops and irrigation systems by comparing water use on a particular field in different years while controlling for changes in the pumping cost, weather, and macro-level shocks (i.e., \mathbf{X}_{it} and γ_i).

Equation (7) might be violated if a farmer implements a new management practice (such as a new tillage system) that affects both water use and land use in the current period. In this case, land use and the idiosyncratic error would be contemporaneously correlated, but the error would still have zero mean conditional on previous land use, $E[\varepsilon_{it} | \mathbf{X}_{i1}, \dots, \mathbf{X}_{iT}, \mathbf{D}_{i1}, \dots, \mathbf{D}_{it-1}, \alpha_i, \gamma_i] = 0$. To test for this possibility, we computed a Hausman statistic where the alternative model was a first differenced regression using twice lagged land use variables as instruments for current land use, which Wooldridge (2002, p. 308) shows is a consistent estimator in the case of contemporaneous endogeneity. The test, reported in the sensitivity analysis section, narrowly fails to reject the null model assuming contemporaneous exogeneity.

Note that conditional strict exogeneity does not preclude previous land use from being correlated with current land use. Certainly, crop rotations are a primary determinant of crop choice and the irrigation systems are an investment decision, implying that changes in current land use affect land use during future periods.

Recovering the Indirect Intensive Margin

We have shown above that the regression estimates from equation (5) identify the total intensive margin effect while estimates from equation (6) identify the direct intensive margin effect. A comparison of equations (5) and (6) suggests the difference arises from omitted variables in equation (5), namely the land-use variables \mathbf{D}_{it} . By relying on the formula that quantifies omitted variable bias, we next show that the difference of these coefficients is precisely the indirect intensive margin effect as conceptualized in the second term of equation (4) and that it is implicitly defined through a linear probability regression in our empirical model.

Let \mathbf{Z}_{it} denote a row vector of time dummies and explanatory variables for observation it in equation (5) and let \mathbf{Z} denote the matrix containing all observations where each row of \mathbf{Z} corresponds to a particular row vector \mathbf{Z}_{it} . Now we can rewrite equation (5) as $\tilde{\mathbf{w}} = \tilde{\mathbf{Z}}\theta_u + \tilde{\varepsilon}$ and equation (6) as $\tilde{\mathbf{w}} = \tilde{\mathbf{Z}}\theta_c + \tilde{\mathbf{D}}\delta + \tilde{\varepsilon}$, where tilde (\sim) denotes variables differenced from the mean for each field and farmer, the subscripts u and c denote the unconditional and conditional parameters as before, and $\tilde{\mathbf{w}}$ and $\tilde{\varepsilon}$ denote the mean-differenced vectors of all observations of w_{it} and ε_{it} . The omitted variable bias formula in our application is (Cameron and Trivedi, 2005):

$$(8) \quad \hat{\theta}_u = \hat{\theta}_c + (\tilde{\mathbf{Z}}'\tilde{\mathbf{Z}})^{-1}(\tilde{\mathbf{Z}}'\tilde{\mathbf{D}})\hat{\delta} = \hat{\theta}_c + \hat{\pi}\hat{\delta},$$

where $\hat{\pi}$ is the parameter vector from a fixed effects regression of \mathbf{D}_{it} on \mathbf{X}_{it} and γ_i (a linear probability model), and the hat ($\hat{\cdot}$) denotes fixed effects parameter estimates. In other words, an interpretation of the coefficient on the cost of water in the unconditional regression is the change in water use holding land use constant ($\hat{\theta}_c$) plus the change in land use times the change in water use resulting from the change in land use ($\hat{\pi}\hat{\delta}$). An estimate of the indirect marginal effect is $\hat{\theta}_u - \hat{\theta}_c = \hat{\pi}\hat{\delta}$.

Although land-use choices are not explicitly modeled, equation (8) reveals that the indirect marginal effect is identified implicitly with a linear probability model. The linear probability model is appropriate in our example for two reasons. First, we are concerned primarily with identifying marginal effects rather than predicted probabilities. Second, field and farmer-level unobserved

heterogeneity is very important and introducing nonlinearities precludes fixed effects methods to control for unobserved heterogeneity. The linear probability model is recommended by Angrist (2001) as a viable alternative to nonlinear estimators when the objective is to identify marginal causal effects rather than index coefficients.

The linear probability model embedded within equation (8) explains land use in year t with contemporaneous (unlagged) exogenous variables, \mathbf{X}_{it} and γ_t . This embedded model also appears to suffer from omitted variable bias because lagged land use variables are not included. Crop rotations are perhaps the most important factor for crop choice, and irrigation system choice is an investment decision with large fixed costs, which creates resistance to convert irrigation systems.

Once again, applying the omitted variable bias formula gives an interpretation of our results. The coefficient on pumping cost in the linear probability model gives the total change in land use resulting directly from the increase in the cost of water and indirectly from changes in previous land uses. In other words, a change in the pumping cost causes a change in the current land use and this change in the land use will affect future land-use decisions. The coefficients on the pumping cost in the fixed effects land use regressions identify the sum of these two effects.

Water Demand Estimates

Parameter estimates from the unconditional reduced form fixed effects regressions are reported in columns (1) and (2) in table 2. A \$1/acre-inch increase in the cost of pumping causes a reduction in irrigated acreage from a well by 1.95 acres on average and decreases water applied by 1.49 acre-inches per acre.

All parameters were significant at a 1% level and of the expected sign. The model explains very little of the within-panel variation of irrigated acres. However, the unconditional model explains 13% of the within variation of applied water per acre. We find this satisfactory given that a substantial portion of the variation in acreage and applied water per acre is due to between-panel variation explained by the panel fixed effects.

The precipitation and ET variables are measured with error, as they are meant to represent field-level weather conditions but are observed only at a representative weather station in each crop reporting district. This measurement error will lead to attenuation bias in the estimated coefficients on precipitation and ET and a lower R^2 . However, estimated coefficients on other variables are asymptotically unbiased if the other variables are orthogonal to actual precipitation and ET (Wickens, 1972). The variation in precipitation and ET within a district in a given year does not have any relationship with the depth to water. Therefore, even though the coefficients on precipitation and ET are biased towards zero, the coefficient on the cost of pumping in our model will remain asymptotically unbiased. Indeed, the coefficient estimates on weather variables in table 2 are smaller than expected but are of the correct sign and statistically significant.

Table 3 reports the intensive and extensive margin elasticities at the means which are computed from the coefficients in table 2. Standard errors are calculated by the delta method. Our estimate of the total elasticity of demand is -0.10, which is highly inelastic.¹⁰ Our estimated total elasticity is consistent with previous literature on water demand (Scheierling, Loomis, and Young, 2006), although still lower than the average estimate.

The estimated intensive margin elasticity of -0.09 implies that most of the response occurs at the intensive margin, through changes in applied water per acre, while the extensive margin elasticity is only -0.01. The extensive margin response is likely small because incrementally altering the irrigated acreage of a particular field can require substantial costs for center pivots.¹¹ In the next section, we

¹⁰ We also obtained an estimate of total elasticity of demand by regressing total water consumption, q_{it} , on the cost of pumping and obtained a very similar result.

¹¹ Changing irrigated area from center pivots requires mechanical alterations to the system to reduce the arc of coverage. Such changes typically require significant labor and expertise.

Table 2: Parameter Estimates for Water Demand

Variables/Statistics	Acres	Applied Water per Acre	
	(1)	(2)	(3)
Pumping Cost	-1.95** (0.362)	-1.49** (0.118)	-1.34** (0.108)
Jan-April Precip		-0.20** (0.018)	-0.20** (0.017)
May-Aug Precip		-0.08** (0.004)	-0.08** (0.004)
May-Aug ET		0.07** (0.009)	0.07** (0.009)
Corn			0.14 (0.122)
Soybeans			-0.18 (0.130)
Wheat			-4.83** (0.162)
Sorghum			-2.71** (0.164)
Other			-4.33** (0.195)
Multiple			-1.46** (0.134)
Double-crop			-0.50** (0.166)
Furrow			2.14** (0.144)
Standard CP			-0.07 (0.064)
R^2 Within	0.002	0.130	0.193
Observations	152,654	152,654	152,654

Notes: The dependent variable is given by the column heading. Standard errors are in parentheses. * and ** denote significance at the 5% and 1% levels. The regressions control for field-farmer and year fixed effects. Coefficient estimates on year fixed effects are not reported.

re-estimate the model with alternative subsets of the data and find that our results of highly inelastic demand and a small extensive margin response are robust across subsets of the data.

Coefficient estimates in column (3) of table 2 are the conditional estimates corresponding to equation (6). As expected, the coefficient on pumping cost is smaller in the conditional regression, -1.34, compared to the unconditional regression estimate of -1.49 in column (2).

The coefficients on the crop variables, where the base crop is alfalfa, are all intuitive. Corn, alfalfa, and soybeans all emerge as “water intensive crops,” with statistically insignificant irrigation intensity rate differences. Wheat, sorghum, and other crops are the least water intensive crops, with significant and negative coefficients. When the only information given is that multiple crops were planted, the water use is significantly less because less water intensive crops were likely among the crops planted. Less water is applied when the field is double-cropped. Kansas’ growing season makes it agronomically difficult to double-crop with corn, so double-cropping typically occurs with less water intensive crops.

The coefficients on the irrigation systems in table 2 identify the effect on applied water use per acre from converting irrigation systems holding crop choice constant. All else constant, irrigators

Table 3: Decomposed Elasticity of Demand Estimates

Effects	Elasticity
Intensive	-0.09 (0.007)
Direct	-0.08 (0.006)
Indirect	-0.01 (0.009)
Extensive	-0.01 (0.002)
Total	-0.10 (0.007)

Notes: Standard errors are in parentheses.

who converted from furrow irrigation to low drop nozzles on average reduced their water applied by 2.14 inches per acre, a substantial water savings. However, converting from standard center pivot to low drops did not significantly affect water use. Our empirical results are consistent with the theoretical results of Zilberman (1984) and Caswell, Lichtenberg, and Zilberman (1990); more efficient irrigation systems reduce water use given inelastic demand.

Table 3 reports the direct and indirect intensive margin elasticities. The direct effect corresponds to the coefficient on pumping cost from column (3) in table 2, and the indirect effect corresponds to the difference in the coefficients between columns (2) and (3).

Most of the intensive elasticity is due to the direct effect (i.e., very little adjustment occurs due to changes in crops and irrigation systems). We examined the linear probability regressions, which are implicitly embedded in our model, to gain a greater understanding of this result.¹² When the cost of pumping increases, the probability of planting corn decreases and the probability of planting alfalfa increases. Farmers apply slightly more water on corn than alfalfa, *ceteris paribus*, as indicated by the positive coefficient on corn in table 2. Thus, farmers reduce acreage of the most water intensive crop, corn, when the cost of pumping increases. The reduction in corn acreage is accompanied by a small reduction in soybean and sorghum acreage, which are commonly planted in rotation with corn, even though these crops are relatively less water intensive than alfalfa. The increase in alfalfa acreage largely negates the reduction in applied water from a decrease in corn acreage.

The linear probability regressions indicate that an increase in the pumping cost decreases the probability of furrow irrigation and increases the probability of both center pivot systems. However, the effects were relatively small, resulting in little water conservation. Incentives to adopt low drop nozzles include an increase in the application efficiency, a reduction in labor costs relative to furrow, and a reduction in the application cost of water relative to standard center pivot.¹³ These incentives are likely the primary reasons for converting irrigation systems, rather than increases in the cost of pumping.

Sensitivity Analysis

First, we explore alternative explanations for the highly inelastic demand estimate and relatively small extensive margin effect. One possible explanation is that the water allocation on an irrigator's water right creates a binding constraint on irrigated acreage, which would lead to a marginal

¹² Estimates from the linear probability regressions are not reported, but are available from the authors upon request.

¹³ The increase in application efficiency reduces the per unit cost of effective water use since less water is lost to evaporation and runoff.

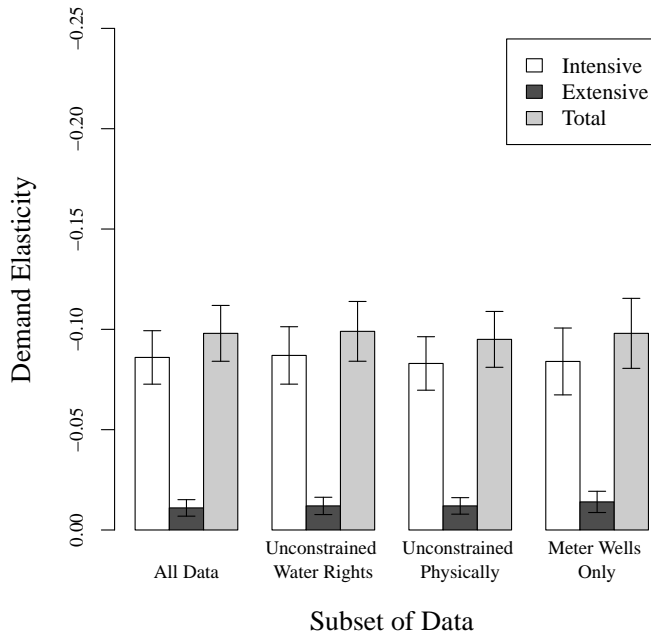


Figure 2: Elasticities with 95% Confidence Intervals for Alternative Subsets of Data

response to price of zero. The second group of estimates in figure 2 are obtained after removing all observations with water use within 10% of the water right allocation.¹⁴

We also investigate whether physical limits on pumping, which would limit the ability to expand acreage and irrigate at the profit-maximizing intensity, affect our elasticity estimates. The third group of estimates are from a subset of data excluding all townships where the Kansas Geological Survey estimates that the aquifer cannot sustain pumping of 400 gallons per minute or greater—the threshold often thought necessary to irrigate at full capacity. Finally, we investigate whether our elasticities are biased due to measurement error from farmers’ self-reported pumping rates; on wells with no meter, water use is usually calculated from the farmer’s reported days of pumping and average daily pumping rate. The subset of data for the fourth group of estimates includes only observations whose water use was measured with a meter.¹⁵

The elasticity estimates in figure 2 differ very little across the alternative subsets of the data. Thus we are confident that our elasticity estimates are not substantially affected by legal, physical, or data constraints.

Next, we explore whether the small estimate of the indirect intensive margin effect is sensitive to the model specification. As mentioned previously, we do not know what proportion of a field is planted to each crop when a field is split between two or more crops. This measurement error may bias our estimate of the indirect effect. In figure 3, we report direct and indirect elasticity estimates when only fields with a single crop are included in the sample. The total intensive margin elasticity estimate is slightly smaller for those fields where only a single crop was planted, but the indirect effect is very similar. The smaller total intensive margin elasticity is likely due to the fact that those farmers who only planted a single crop are a distinctly different sub-sample.

¹⁴ This calculation is based on water right data for 2006, the only year for which water right data were available to us. However, water rights generally change little over time.

¹⁵ We also drop observations before 1997 because there were very few meters until 1997. The drastic imbalance of observations in early years skewed the estimates.

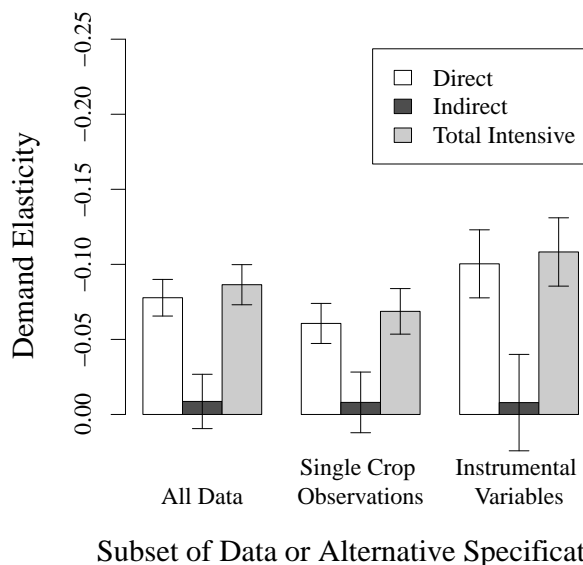


Figure 3: Alternative Direct and Indirect Intensive Elasticities and 95% Confidence Intervals

If farmers changed management practices during the sample period this could induce contemporaneous endogeneity between land use and water use. We report estimates where we correct for this problem by first-differencing the data and using twice lagged land use as instruments (figure 3). Again the indirect effect is very similar to our fixed effect estimate. The total intensive margin elasticity is estimated by first-differences and therefore differs from our mean-differenced estimate. We test our specification more formally by computing a Hausman statistic where the variance was estimated with 400 bootstraps and obtain a test statistic of 33.71 compared to the critical value of 36.42.¹⁶ Therefore, we narrowly fail to reject the null hypothesis of contemporaneous exogeneity of land use. In any case, as shown in figure 3, correction for this problem has little effect on our results.

Cost-Effectiveness of Water Management Policies

The policy relevance of our estimates is illustrated by calculating the cost of three types of commonly discussed policies to reduce agricultural water consumption. Here, we sidestep the larger question of the public benefits of reducing water allocated to agriculture and appeal to the standards approach of Baumol and Oates (1988), where the policy goal is taken as given and we determine the cost of alternative policies to achieve that goal.

We compare the cost of water pricing, irrigation cessation, and intensity reduction programs. In practice, irrigation cessation and efficiency improvement programs typically have been implemented as subsidies to farmers while water pricing would likely be imposed as a costly tax on farmers. For ease of comparison, we envision a pricing program in which each farmer receives a lump-sum transfer from the government to compensate for the lost producer surplus from the increased water price. Even if such transfers do not occur, however, the costs can still be compared as overall losses in producer surplus, whether these losses are borne by taxpayers or by farmers.

In what follows we interpret $q(p) = a(p)w(p)$ as the total water demand of the representative irrigated tract among a large population of such tracts in some region. As shown in figure 4, the current price of water is p_0 , leading to a total demand of $q_0 \equiv q(p_0) = a(p_0)w(p_0)$, where $a(p_0) \equiv a_0$

¹⁶ We bootstrap the variance because neither of our estimators are fully efficient (see Cameron and Trivedi, 2005, p. 378).

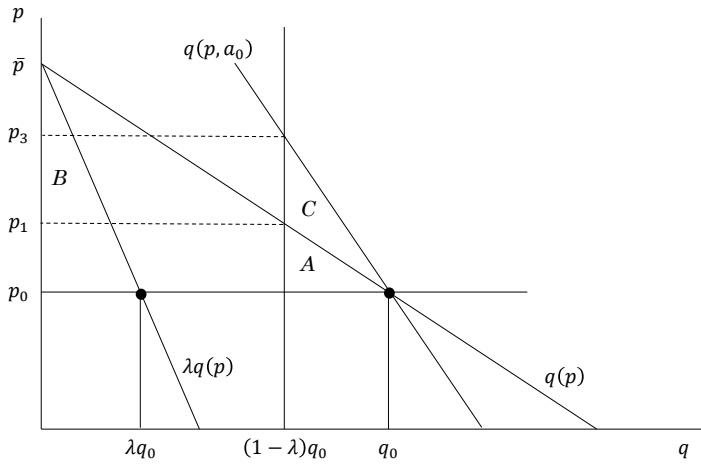


Figure 4: Geometry of Cost-Effectiveness of Three Policies

is current irrigated acreage and $w(p_0) \equiv w_0$ is current water demand per acre. The policy goal is to reduce total water consumption by some fraction, λ , of current water use.

The first type of policy we analyze is water pricing which reduces water use by $\lambda \times 100\%$. Let p_1 denote the price of water after the tax; i.e., $q(p_1) = (1 - \lambda)q_0$. The reduction in producer surplus due to the tax is calculated as:

$$(9) \quad c_1 = \int_{p_0}^{p_1} [q(p) - (1 - \lambda)q_0] dp,$$

which is area *A* in figure 4.

A second type of policy is an irrigation cessation program in which irrigated acreage is reduced to zero on some fraction of tracts. This class of policies includes “water right retirement” programs as well as those where irrigation is suspended temporarily. For example, the Conservation Reserve Enhancement Program (CREP) pays annual rents to landowners who convert irrigated cropland to a conservation use for a 10- or 15-year period. State-federal partnerships currently fund such CREP programs in both Nebraska and Kansas (Dunnigan, 2009; Kansas State Conservation Commission, 2009). Assuming these programs enroll representative tracts then exactly a share λ of the tract population will cease irrigation. Letting \bar{p} denote the choke price of the demand function (i.e., $q(\bar{p}) = 0$), the cost of irrigation cessation is:

$$(10) \quad c_2 = \lambda \int_{p_0}^{\bar{p}} q(p) dp,$$

which is area *B* in figure 4. Here, the entire surplus under the demand curve is lost for the fraction of tracts removed from irrigation.¹⁷

A third type of program takes various forms but targets a reduction in applied water per acre, $w(p)$, while leaving irrigated acreage fixed at a_0 . Perhaps the closest existing analog of this approach is the federal Environmental Quality Incentives Program (EQIP), which pays cost-share subsidies to irrigators in the High Plains to adopt intensity-reducing irrigation management practices such as irrigation scheduling. This analogy is not perfect, however, because EQIP is a practice-based rather than a performance-based program. A practice-based program would be conceptually equivalent to this class of policies only if the practice (or suite of practices) it induces on each tract is the least-cost

¹⁷ Naturally, if the enrolled tracts are not representative and have a smaller (larger) cost than the representative tract, then the expected loss in producer surplus would be less (greater) than area *B*. The representativeness of enrolled tracts would depend on the details of program design.

way of obtaining the prescribed reduction in w . Let $q(p, a_0) = a_0 w(p)$ denote the conditional water demand function when acreage is fixed at a_0 . As shown in figure 4, this function passes through the point (p_0, q_0) but is more inelastic than $q(p)$ because as prices change only the $w(p)$ component of water demand is affected. Let p_3 denote the price such that $q(p_3, a_0) = (1 - \lambda)q_0$. The cost of this policy is:

$$(11) \quad c_3 = \int_{p_0}^{p_3} [q(p, a_0) - (1 - \lambda)q_0] dp,$$

which is the sum of areas A and C in figure 4.

As can be seen from figure 4, water pricing is the least-cost means of achieving the policy target. In the case of a linear total water demand, water pricing is a fraction, λ , of the cost of irrigation cessation programs. When λ is small, irrigation cessation programs are relatively more costly. Intuitively, this result holds because it is less costly for irrigators to reduce their water use by the first acre-inch than the last acre-inch. The cost of water pricing compared to an intensity-reduction program depends on the slope of the demand curve holding acreage fixed relative to the slope of the total demand curve. A large extensive margin effect implies a large cost savings from water pricing. The cost of irrigation cessation compared to intensity reduction depends on the slope of the two demand curves and the desired reduction in water demand.

Conservation Cost Estimates

Using our empirical estimates of the demand for irrigation water, we calculate the cost of reducing applied irrigation water for the three different policy instruments. We calculate the cost of each instrument for the cross-section of fields present in our (unbalanced) panel in the year 2000. For each of these fields we calculated the cost of pumping using the average natural gas price from our entire sample and the field-specific depth to water in 2000. We assume average precipitation and ET from the sample for each district and use the average coefficient on the year dummy variables. The cost of the policy instruments are calculated for every field and then averaged across the cross-section. As such, our estimated costs reflect the costs for the 2000 cross-section of fields under average price conditions across the entire data period. The predicted total water demand before and after the policy are summed across all fields to obtain the percent reduction in demand from the policy.

To calculate the costs for each field, we must explicitly calculate the total water demand both before and after the policy along the $q(p)$ function, which requires field-specific prices and estimates of all the demand parameters including the intercepts.¹⁸ We use the fixed-effect field-level intercept estimates, which are inconsistent at the field level (Cameron and Trivedi, 2005, p. 733). Although we cannot consistently estimate the effects on producer surplus for each field, by the law of large numbers we still obtain a consistent estimate of the average effect.¹⁹

In order to make the cost easier to interpret we divide the cost by the acre-inches of water reduced to obtain the cost per acre-inch and also divide the cost by the predicted pre-policy acreage to derive a cost per acre. The per acre cessation cost is calculated with the predicted total pre-policy acres irrigated rather than the acres in the cessation program. The cost of each instrument is an annual cost. Results are shown in figure 5 for alternative reductions in aggregate water demand. We predict that the average cost of ceasing all water rights is \$64 per acre per year, which should approximately be the difference in irrigated and nonirrigated cash rent. The difference in irrigated and nonirrigated district-level cash rent for 2009 was \$65.50, \$53, \$55, and \$55 for the northwest,

¹⁸ Note that the estimated total water demand curve is quadratic (the product of the linear $w(p)$ and $a(p)$ functions).

¹⁹ As a robustness check, we found similar results using an "average" field-level intercept for each cost of pumping which is the prediction from a cubic regression of the field-level intercepts on the cost of pumping. We chose a high order polynomial regression in order to avoid imposing a strict parametric relationship between the intercept and initial cost of pumping.

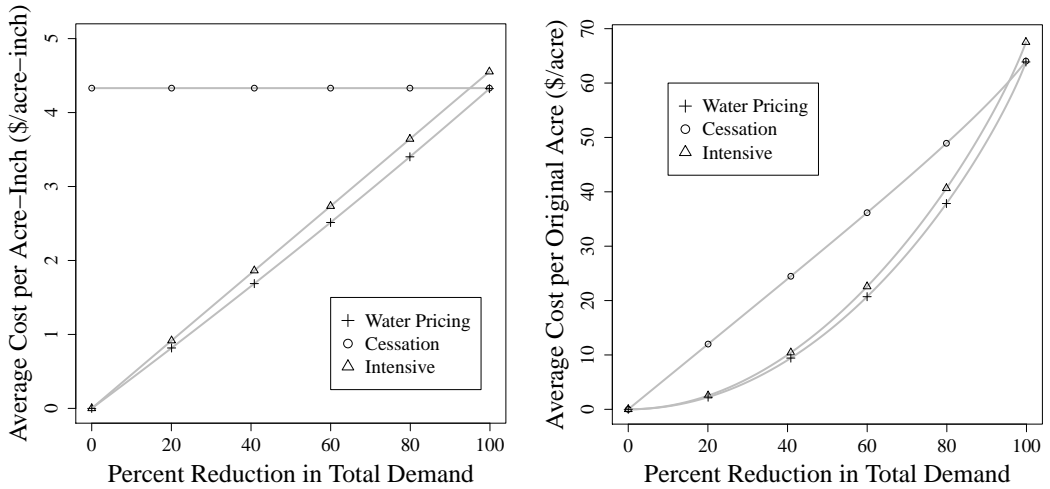


Figure 5: Cost of Implementing Alternative Water Reduction Policies

westcentral, southwest, and southcentral districts (National Agricultural Statistics Service, 2009). Thus, our estimates of irrigation water demand seem very reasonable.

The cost of a cessation program far exceeds the cost of water pricing when the reduction in water demand is small, as evidenced by the large difference in the cost per acre-inch. A program to reduce water demand per acre is nearly as cost-effective as water pricing because we find that the extensive margin elasticity is relatively small. For a very large reduction in water demand, the cost of an intensive margin program exceeds the cost of a cessation program because we assume farmers are not allowed to reduce irrigated acreage.

In 2009, the Kansas State Conservation Commission was appropriated \$3.45 million for the Kansas CREP and Water Transition Assistance Program (WTAP), the two active water right retirement programs in the state (Kansas State Conservation Commission, 2009). We consider the annual reduction in water demand that could be achieved at an annual cost of \$3.45 million. Our estimates indicate that they could reduce water demand by about 66,390 acre-feet using a cessation program. The Kansas Department of Agriculture reports that irrigation water use in 2007 was 3,061,922 acre-feet. Thus, such a cessation program should be able to reduce water use by about 2.17% annually. Alternatively, if the State Conservation Commission had spent this budget to pay lump-sum transfers to compensate irrigators for their production losses from a water pricing program, their budget would have been sufficient to compensate for about a 15% reduction in water demand.

Conclusions and Policy Implications

This paper illustrates a fixed effects approach to estimate and decompose the elasticity of demand for a factor of production. The method was applied to field-level panel data on groundwater pumped for irrigation in the High Plains Aquifer region of Kansas. Controlling for field-farmer and year fixed effects gives us robust estimates. The coefficient on pumping cost is identified because when the price of natural gas increases, the cost of pumping increases more in areas that have a greater depth to water.

Although the estimation technique was applied here to irrigation water demand, it is also applicable to other situations where input use varies cross-sectionally due to site-specific factors that cannot be easily observed and can be subsumed into a fixed effect. In agriculture, the model is

applicable to the demand for other crop inputs including fertilizer, chemicals, and fuel. It also applies to estimation of input demand by other industries in cases where input decisions are conditioned on unobserved cross-sectional factors. An additional advantage of the approach is that it corrects for the potential correlation between a firm's decisions about their output mix and their input intensity to produce each output, generating an unbiased decomposition of intensive and extensive margin effects. Such estimates are needed to evaluate the many policies that aim to reduce input use through incentives to change the mix of production or production techniques.

The demand elasticity for irrigation water in the High Plains, -0.10 , is highly inelastic. Most of the adjustment in water applied occurs at the intensive margin (changes in the water applied per acre). Possibly, the reason for such an inelastic estimate is because the number of wells is constrained due to water rights. A new water right can only be issued if it does not impair a previous water right. If the number of wells were unconstrained, the extensive margin effect would certainly be larger and increase the total elasticity estimate. However, we find that the constraints imposed by the water quantity allocations on individual water rights do not affect our estimates.²⁰

Our results have several implications for water management policies in the High Plains and for the ways in which energy markets and agricultural conservation programs are likely to impact water use. First, the highly inelastic nature of the demand for groundwater withdrawals for irrigation implies that long-term increases in energy costs, whether induced by climate policy, energy scarcity, or increased pumping lifts, will have a negligible impact on water consumption. To the extent that water does adjust, it will be mostly through farmers' adjustments in intraseasonal management. Irrigated area, crop choices, and irrigation systems will remain stable in the face of increased water withdrawal costs in the short-run, *ceteris paribus*.

We compare three different conservation programs to reduce agricultural water use: water pricing, irrigation cessation, and intensity reduction programs. At an annual cost of \$3.45 million, our estimates indicate that the state of Kansas could reduce water use by about 15% with water pricing, as opposed to only reducing water use by 2.17% with cessation programs. This is especially relevant given the introduction of the Water Transition Assistance Program (WTAP) and Conservation Reserve Enhancement Program (CREP) in Kansas to retire water rights.

Because the extensive margin elasticity is relatively small, a program to reduce water use per acre is nearly as cost-effective as water pricing. However, this assumes the program is performance based and gives incentives for the least-cost method of reducing water intensity. In practice, EQIP and other programs that have subsidized technologies or practices have not been performance based.

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²⁰ Here we distinguish between the two forms of constraints that water rights impose: the constraint of obtaining a water right in the first place, and then the constraint of the total quantity of water an irrigator is allowed to pump if they have a water right.

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