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Price elasticity reconsidered: Panel estimation of an agricultural water demand function

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Price elasticity reconsidered: Panel estimation of an agricultural water demand function

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[1] Using panel data from a period of water rate reform, this paper estimates the price elasticity of irrigation water demand. Price elasticity is decomposed into the direct effect of water management and the indirect effect of water price on choice of output and irrigation technology. The model is estimated using an instrumental variables strategy to account for the endogeneity of technology and output choices in the water demand equation. Estimation results indicate that the price elasticity of agricultural water demand is −0.79, which is greater than that found in previous studies.

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1. Introduction

[2] Agricultural producers use the majority of water in the western United States and in many arid regions of the world. As a result of rapid population growth and increasing concern about the environmental effects of surface water diversions, these water users are under increasing pressure to conserve water. Financial incentives, whether embodied in water trading opportunities or increased water rates, are widely touted by economists as an effective means of reducing water consumption in agriculture [*Dinar and Letey*, 1991; *Moore et al.*, 1994]. However, it is sometimes postulated that the price of water delivered to farmers is so highly subsidized that there is no significant demand response to modest price changes [*Garrido*, 2002; *Jones*, 2003]. Missing from this important policy debate are sound estimates of the price elasticity of farm water demand.

[3] Using an estimation methodology that reflects the importance of capital investment, we show that the price elasticity of agricultural water demand is greater than previous studies have found. This paper is an important addition to the agricultural water demand literature for several reasons. Our data are highly disaggregated, allowing us to make better use of important land quality characteristics as explanatory variables. It also includes a panel series of individual sections of land with observations before and after a significant rate change. In addition to the data improvements, we use a novel approach to estimate land allocation (defined as the joint choice of crop and irrigation technology) which corrects for the potential endogeneity of these choices. Our methodology also recognizes the importance of the substantial costs of adjustment that exist for changes in capital stock. Choices of outputs and production technologies are assumed to adjust over time, and thus a water price shock will have long-run effects through its influence on output and technology choice that will be distinct from the short-run effects that incorporate mainly management changes. We find evidence of increased levels of fallow land and the adoption of precision irrigation technologies with higher water prices. We also find evidence of a large cost of adjustment in changing land allocation. These results show that expectations of a farmer's response to higher water prices must be conditioned on current land allocation, as well as land quality characteristics.

[4] Many previous studies of agricultural water demand rely on simulated data and linear programming techniques [*Bontemps and Couture*, 2002; *Hooker and Alexander*, 1998]. In general, these studies consider an individual's response to changes in the price of water under varying conditions. Previous econometric studies of agricultural water demand have found varying results. *Nieswiadomy* [1988] found a price elasticity of water demand of −0.25, while *Moore et al.* [1994] found no short-term response to increased water rates. Despite the lack of a short-term response, *Moore et al.* [1994] do find a significant intermediate and long-term responses through the effect of water price on cropping patterns and extensive margin effects. Our study uses an econometric analysis to decompose water use by both crop and irrigation technology, something not done in previous econometric studies of water demand [*Moore et al.*, 1994; *Ogg and Gollehon*, 1989]. We find a price elasticity of demand of −0.79, which includes both the direct effect of improved water management and the indirect effect of changes in crop or irrigation technologies.

[5] Programming models are frequently used to study urban water demand as well [*Lund*, 1995; *Jenkins et al.*, 2003], although due to better data availability, most previous econometric studies of water demand have analyzed urban water demand, using either residential or industrial water use data. One general result from these studies is that water demand is price inelastic, with the absolute value of the estimated price elasticities generally below 0.5

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[*Hanemann*, 1998]. In a meta-analysis of residential water demand, *Dalhuisen et al.* [2003] find a mean price elasticity of demand of -0.41, while *Espey et al.* [1997] find a median short-run price elasticity of -0.38, and a median long-run price elasticity of -0.64. Many of the recent papers in the study of urban water demand have focused on estimation under block rate pricing, and the implications of appropriately accounting for both the discrete choice of which block to choose, and the continuous choice of how much water to use [*Hewitt and Hanemann*, 1995; *Dalhuisen et al.*, 2003]. This work has found that estimating urban water demand using the discrete-continuous approach finds a much more elastic price elasticity of demand than studies which do not explicitly model both choices. While this type of pricing is common in urban water rates, it is extremely rare in irrigation water rates, and therefore has not been studied in an agricultural context. Another area of research in the urban water demand literature is on the effects of nonprice conservation programs, such as educational campaigns. *Renwick and Green* [2000] find that these type of programs have a significant effect on residential water demand.

2. Empirical Model

[6] In our econometric analysis we estimate a reduced form model of a conditional water demand function, explaining water use at a particular location as a function of land allocation (output and technology choices), relative prices, and other factors such as environmental characteristics. Our estimation strategy assumes that each land allocation choice has a fixed input/output ratio in the short run, and this ratio is a function of environmental conditions and management inputs. This approach assumes that the durability of physical capital fixes the input/output ratio in the short run, but that the choice of technology will adjust over time to changes in the relative prices of inputs and outputs. Irrigation systems can be modeled using this framework, since they are composed of pipes, valves, heads, and other types of equipment. The choice of crop can also be viewed as a particular type of capital investment, as all crops require a significant investment in specialized farm equipment and human capital, while perennial crops also require capital investment in plant stock.

[7] There are several possible outcomes after an increase in the marginal price of water. One possibility is that a producer substitutes increased management efforts for applied water. Another possibility is that the profitability of water-intensive crops will decrease, and producers will either switch to a less water-intensive crop, adopt precision irrigation technology, or both. Similar types of responses were considered in an analysis of household water demand by *Lund* [1995], where a household's adaptations to shortages in water supply are decomposed into long-run changes in capital stock and short-run changes in management, such as installing a low-flush toilet and taking shorter showers, respectively. Previous studies have shown that an increase in water price leads to the adoption of precision (water conserving) irrigation systems by farmers [*Caswell and Zilberman*, 1986; *Kanazawa*, 1992; *Green et al.*, 1996]. This research also shows that the relative profitability of different types of irrigation technologies is conditional on land quality characteristics. However, with the exception of Kanazawa, these papers assume that crop choice is exogenous in the irrigation technology decisions. Other work has shown that these two choices are highly correlated, and should be modeled simultaneously [*Lichtenberg*, 1989; *Moreno and Sunding*, 2005]. Lastly, it is possible that when the price of water is very high, producers will choose to take land out of crop production, either for a single cropping season or permanently.

[8] One potential econometric problem encountered in estimating a water demand function that is conditional on the choices of technology and output is the endogeneity of these explanatory variables. Using the regression version of the Hausman test of endogeneity of the land allocation variables, we are able to reject the null hypothesis that all land allocation variables are exogenous with a significance level of 1%. Therefore we use instruments for all of these variables to eliminate any potential problems with endogeneity. We use an estimation similar in spirit to a 2SLS estimation, where we estimate the area in each land allocation choice in the first stage, and then use those fitted values to estimate the second stage water demand equation. However, we also account for the censoring of the variables we estimate in the first stage with a Tobit analysis. The use of a Tobit analysis as a consistent estimation strategy for a censored demand system has been used frequently, and has been well established in recent literature [*Shonkwiler and Yen*, 1999; *Coxhead and Demeke*, 2004; *Yen*, 2005; *Meyerhoefer et al.*, 2005].

[9] The estimation of the water demand equation uses panel data which raises several other issues. The panel includes 117 sections of land over 8 years. One potential problem is heteroscedasticity. If the variation in errors is due to unobserved characteristics at the section level, we can estimate either a fixed or random effects model. Random effects models assume that the error term can be divided into the 'true' error and another term unique to a specific group in the sample. However, for random effects to be valid, the error terms must be uncorrelated with the explanatory variables. A test of our data shows that this assumption does not hold. The fixed effects model allows for correlation between the error terms and the explanatory variables, but it limits the choice of variables. Because a fixed effects model examines the differences within a group over time, the impact of individual-specific variables (such as land quality characteristics) that remain constant cannot be identified. In addition, a fixed effects estimation assumes that land management remains constant over the entire time series. This is not the case if an owner decides to sell or lease his/her land. Instead, we use a generalized least squares (GLS) estimation to allow for heteroscedastic error terms and we also correct for autocorrelation in our estimation of water demand.

2.1. Water Demand Estimation

[10] The main equation we estimate is the water demand equation, where water demand is a function of water price, section-specific variables, and time-specific variables as shown below in equation (1). We estimate total water use in section i at time t (W_{it}^D), as a linear function of the

Table 1. Number of Sections Choosing a Crop and Irrigation Combination (2001)

Crop Type	Irrigation Type	Number of Zero Observations	Number of Nonzero Observations
Fallow	–	15	102
Citrus	drip	70	47
Citrus	gravity	114	3
Grape	drip	74	43
Grape	gravity	88	29
Deciduous	drip	94	23
Deciduous	gravity	104	13
Deciduous	sprinkler	105	12
Truck	gravity	108	9
Truck	sprinkler	65	52
Field	sprinkler	67	50

explanatory variables as follows, although a log function estimation yielded similar results:

$$W_{it}^{D} = \gamma_0 + \gamma_1 X_t + \gamma_2' \alpha_i + \gamma_3' \widehat{a}_{it} + \gamma_4 p_{wt} + \epsilon_{it}, \tag{1}$$

$$\text{where } \epsilon_{it} = \rho \epsilon_{it-1} + \nu_{it},$$

$$\text{and } \nu_{it} \sim \eta\left(0, \sigma_i^2\right).$$

The variables included in the analysis are time-dependent variables (average yearly temperature, marginal water price, fuel prices and farm labor wage), land quality variables (slope, soil permeability, and average section temperature), and predicted land allocation. The method used to estimate the predicted land allocation ($\widehat{a}_{it}$) is described in Section 3.2. The marginal water price is the variable of most interest in this study. As there are few substitutes for effective water in crop production, we do not include prices of other nonwater and nonlabor farm inputs such as fertilizers and pesticides [see, e.g., *Hanks et al.*, 1969; *Power et al.*, 1973].

2.2. Estimation of Land Allocation Instruments

[11] The underlying economic model considers the amount of land available as a fixed input into production, and requires a farmer to choose the appropriate allocation of land, conditional on relative input and output prices. We assume that each choice of crop and irrigation technology has an optimal level of water application and management associated with it, and that these optimal levels are conditional on the relative price of water to farm management, as well as the expected output prices for different crops. Relative profitability, and therefore the optimal allocation of land, are influenced by a number of factors including the quality of the land, the existing land allocation, as well as relative input and output prices. For example, farmers with highly sloped land earn a greater benefit from drip irrigation than farmers with flat land, even when facing identical input and output prices. We use these results to inform our estimation equations and the variables employed in those equations.

[12] Previous work has often used a discrete choice model to estimate the crop or technology on a particular field, where a field is defined as a contiguous area planted with the same crop and irrigation technology [*Green et al.*, 1996; *Moreno and Sunding*, 2005]. However, we do not observe water use at the field level, only the total quantity delivered to each section. In addition, for certain years the land allocation data is only available aggregated by section. Therefore we use a model of land allocation which considers total available land as fixed allocatable input into production.

2.2.1. Estimation of Land Allocation Totals

[13] The estimation of land allocation totals includes many observations with zero area. Table 1 shows the prevalence of this in 2001, but is representative of all of the other years. Although this outcome is the result of corner solutions (as opposed to censored values), this type of model can be consistently estimated using a Tobit estimation strategy [*Wooldrige*, 2002]. The estimation strategy also imposes an upper bound on the estimated values, requiring that the predicted values do not exceed total available land.

[14] In our estimation strategy, we account for the importance of previous land allocation. We assume that a farmer in each period has the option to keep his/her existing land allocation or to alter those decisions. There are costs of adjustment, which are incurred both when land is moved into a new use, and out of an existing one. The level of these costs will depend on the crop and technology employed, but with perennial crops such as citrus trees, both of these costs are considerable. Because of these costs of adjustment, a producer will only alter his/her land allocation if the change in expected profit is greater than the cost of that change. Therefore we expect that small changes in the marginal price of water may not affect land allocation choices, but that with a significant jump in the price we will observe land allocation adjustment. This is consistent with anecdotal evidence that farmers are more likely to adjust their crop choice and irrigation equipment in years when there is a drought.

2.2.2. Land Allocation Estimation Strategy

[15] In the following formulation, we let a_{ijt}^{*} be the underlying latent variable, a_{ijt} denote the observed (censored) area, a_{it-1} as the Jx1 vector of all the lagged values, α_i the vector of section specific variables, p_{mt}, p_{wt}, and p_t the management cost, marginal water price, and vector of lagged output prices respectively. For each crop/technology pair j = 1,. . .,J we estimate:

$$a_{ijt}^{*} = \beta_{0j} + \beta_{1j}' \alpha_i + \beta_{2j} p_{mt} + \beta_{3j} p_{wt} + \beta_{4j}' p_t + \beta_{5j}' a_{it-1} + \epsilon_{ijt}. \tag{2}$$

[16] We make the typical assumptions of a Tobit model, which include the following:

$$E[a] = \begin{cases} a^{*} & \text{if } \beta' x + \epsilon \geq 0 \\ 0 & \text{else.} \end{cases} \tag{3}$$

and:

$$\epsilon_{ijt} \sim \eta\left(0, \sigma_j^2\right). \tag{4}$$

[17] Equation (2) includes time specific variables (output prices, marginal water price, annual temperature, fuel prices and farm labor wage), land quality variables (slope, soil

Table 2. Summary of Water Prices, 1994–2001[a]

Year	Fixed Cost	Variable Cost
1994	340.8	36.7
1995	235.0	53.0
1996	235.0	53.0
1997	235.0	53.0
1998	200.0	52.6
1999	200.0	41.2
2000	200.0	41.2
2001	145.0	41.2

[a]Fixed costs are paid per hectare, while variable costs are paid per thousand cubic meters. Prices are given in dollars.

permeability, average section temperature, and frost-free days), as well as lagged land allocation values. An increase in the price of water will lead to less area planted with traditional irrigation technology, and therefore we expect the coefficient on water price for those choices to be negative. However, for land in precision irrigation technologies, the sign of the coefficient is difficult to predict. There are two effects that need to be considered. The first is that an increase in water price will lead to higher levels of fallow land, which decreases the overall amount of land in production. The second effect is that the relative profitability of precision technology over traditional irrigation increases with higher water prices, and thus implies a switch from traditional irrigation methods into precision technologies. The question of which effect is greater needs to be examined empirically.

[18] Each of the land quality variables affects what type of crop can be grown, which irrigation systems can be used at a particular location, as well as the relative profitability of each crop and irrigation system. For example, crops with a low frost tolerance are less likely to be planted in areas with a low number of frost-free days. Precision irrigation systems are relatively more profitable on land with a high slope, as the gains in input use efficiency are greater than on flat land. Therefore these variables affect both the initial land allocation choices, as well as the decision to adjust that allocation.

[19] The lagged land allocation variables are included to measure the effect of adjustment costs and the durable nature of technology and output choices. Obviously, perennial crops are durable since they require an established stand of trees or vines. Other sources of adjustment costs in the cropping decision are human capital (i.e., knowing how to grow grapes does not imply that one knows how to grow lettuce), and also that the long-term relationship between a farmer and a distributor of a crop influences the price farmers receive for their output [*Hueth and Ligon*, 1999]. In addition, we expect to observe some element of crop rotation in the annual crops included in the estimations, as it is beneficial for certain crops in the region, such as cotton and carrots, to have rotation between years.

2.2.3. Calculation of Predicted Land Allocation

[20] We note that due to censoring, the predicted value of the observed ratio is not the linear prediction using the estimated parameters. Using Φ to denote the normal cumulative distribution function (cdf), ϕ the normal probability distribution function (pdf), β_j as the estimated coefficients in the jth equation, and σ_j as the estimated standard error, we use the following formula to calculate the expected value of the land allocation totals (the dependent variable):

$$\widehat{a}_{ijt} = E\left[a_{ijt}|X_{ijt}\right] = \Phi\left(\frac{\beta_j' X_{ijt}}{\sigma_j}\right)\left(\beta_j' X_{ijt} + \sigma_j \frac{\phi\left(\frac{\beta_j' X_{ijt}}{\sigma_j}\right)}{\Phi\left(\frac{\beta_j' X_{ijt}}{\sigma_j}\right)}\right). \quad (5)$$

These predicted land allocation variables provide the instruments for the actual land allocation in the water demand estimation.

3. Data

[21] The data used in this analysis come from the Arvin Edison Water Storage District (AEWSD), a utility serving over 52,000 hectares (130,000 acres) and roughly 150 farming operations located 90 miles north of Los Angeles. Of this land, about 46,400 hectares (116,000 acres) are either in agriculture or are potential agricultural land (fallow and idle land), resulting in an average operation size of about 310 hectares (775 acres). AEWSD collects technology and output choice data at the field level, as well as the water price and water delivery data. A water year runs from March until the following February, a time period that parallels the growing season in the district. The district sets the water price at the beginning of each water year, and measures monthly water deliveries at each turnout. A turnout is the endpoint of water deliveries. As a turnout can provide water to multiple fields, it is difficult to accurately calculate the water use per field. There are 444 turnouts in the surface water area, resulting in an average of 3.8 turnouts per section, although the vast majority of sections contain less than 7 turnouts. We aggregate the water delivery data by year and turnout to obtain total water deliveries by section. Combining these with the land allocation data, it is possible to piece together a fairly complete picture of water use decisions at the micro level. While it would be ideal to have this data at the farm management level, we do not have access to the information required to do so, due to agreements with AEWSD. However, it is common in economic analysis to use data at a geographical unit such as a census tract or a pixel instead of a household. Examples in the domestic literature often use the census tract [*Collins*, 2004] or county [*Miller and Plantinga*, 1999]. Other examples in the economic literature on land use in developing countries include work at the municipal level [*Pfaff*, 1999], census tract [*Chomitz and Thomas*, 2003] or at the pixel level [*Cropper et al.*, 2001; *Munroe et al.*, 2002]. One benefit of using section level data in this analysis is that section boundaries are exogenously determined, in comparison to an analysis at the field level.

[22] Despite the fact that we do not have farm manager level data, the data we use is superior to previous work on agricultural water demand, due to the greater level of detail at a more disaggregate level. As mentioned above, previous papers have generally used programming models [*Bontemps and Couture*, 2002; *Hooker and Alexander*, 1998; *Schaible*, 1997]. Econometric estimates by *Kanazawa* [1992] use a much greater level of aggregation. While *Moore et al.* [1994] do use farm-level data in their econometric analysis,

Table 3. Land Allocation Totals Over Time by Crop and Technology[a]

Crop Type	Irrigation Type	1994	1995	1996	1997	1998	1999	2000	2001
Fallow	–	2,711	2,720	2,019	4,606	5,062	4,575	3,958	4,000
Citrus	drip	3,114	3,048	3,135	3,489	3,599	3,760	3,822	3,893
Citrus	gravity	348	362	418	390	390	148	235	235
Grape	drip	2,012	2,098	3,106	2,718	2,758	1,709	1,700	1,802
Grape	gravity	1,868	2,109	2,089	2,099	2,026	1,335	1,674	1,780
Deciduous	drip	1,142	1,217	880	970	1,054	708	686	859
Deciduous	gravity	476	688	581	622	685	729	808	529
Deciduous	sprinkler	824	833	374	441	346	514	309	325
Truck	gravity	731	574	–	614	575	640	728	396
Truck	Sprinkler	5,027	4,508	5,685	2,074	2,717	2,846	2,785	2,902
Field	sprinkler	3,362	3,576	4,079	3,603	2,652	2,726	3,016	3,074
All perennial crops	drip	5,530	5,434	5,796	6,644	6,914	7,745	7,510	7,704
All perennial crops	gravity	2,746	2,947	3,195	3,071	3,039	2,168	2,638	2,823
All perennial crops	sprinkler	824	833	374	441	346	514	309	325
All annual crops	gravity	731	574	–	614	575	640	728	396
All annual crops	sprinkler	8,389	8,084	9,764	5,677	5,369	5,572	5,801	5,976
All	annual	9,120	8,658	9,764	6,291	5,944	6,212	6,529	6,372
All	perennial	10,156	10,299	10,426	10,457	10,852	9,100	9,214	9,364
All	drip	5,530	5,434	5,796	6,644	6,914	7,745	7,510	7,704
All	sprinkler	6,086	6,110	6,301	3,684	3,614	2,808	3,366	3,218
All	gravity	9,214	8,917	10,137	6,118	5,714	3,476	3,521	3,195

[a]Values are in hectares.

the data we use has the advantage of covering an 8-year period, during which there was a rate change in water.

[23] Several factors make AEWSD an appropriate location to study the response to a change in water rates. Because of the nature of the district, many of the confounding factors of studying water demand which exist in other locations are not a concern in AEWSD. In many areas, a shortfall in surface water availability results in producers substituting groundwater for surface water, or using groundwater as the marginal source for irrigation. This creates a problem in measuring both the price paid for water and the quantity consumed. In AEWSD, users are divided into surface and groundwater users, with each being a distinct group. Surface water users are not allowed to dig wells or

Table 4. Summary Statistics of all Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Total water use, 10^3 m^3	1340.02	739.13	1.2	5993.6
Field-level wage, $/h	6.91	0.58	6.2	7.9
Fuel prices, $/million Btu	7.00	1.14	5.7	9.2
Climate characteristics				
Slope, %	1.61	1.23	0.5	9.4
Soil permeability, cm/h	6.71	7.37	0.3	33.0
Average section temperature, °C	17.24	0.26	15.2	18.3
Section frost-free days	270.45	10.35	198.5	275.8
Average annual temperature, °C	18.08	0.36	16.7	18.9
Output price indices (relative to 1993 prices)				
Lagged onion price	109.63	21.10	72.0	140.0
Lagged carrot price	117.13	15.89	100.0	144.0
Lagged potato price	85.00	14.43	63.0	110.0
Lagged cotton price	100.00	13.48	86.0	126.0
Lagged grape price	109.38	7.75	100.0	126.0
Lagged orange price	114.75	22.96	94.0	173.0
Lagged almond price	82.63	26.65	44.0	130.0
Lagged annual price index	101.13	6.05	91.0	111.0
Lagged perennial price index	105.25	8.60	92.0	118.0
Area totals, hectares				
Total area available	146.88	80.11	31.2	331.2
Fallowed area	31.66	45.34	0.0	270.4
Citrus/drip area	29.04	52.67	0.0	252.0
Citrus/gravity area	2.58	13.34	0.0	108.4
Grape/drip area	18.78	36.58	0.0	166.0
Grape/gravity area	16.00	36.13	0.0	211.6
Deciduous/drip area	8.00	26.44	0.0	252.0
Deciduous/sprinkler area	4.07	18.12	0.0	248.8
Deciduous/gravity area	5.43	20.50	0.0	219.2
Truck/sprinkler area	29.23	44.21	0.0	260.0
Truck/gravity area	4.54	17.07	0.0	156.8
Field/sprinkler area	27.52	43.48	0.0	210.0

Table 5. Water Demand Estimation Results[a]

	OLS	Heteroskedastic IV (With AR(1))
Water price	−3.35	−7.64[b]
	(2.60)	(1.54)
Farm wage	43.88	51.64
	(59.06)	(34.33)
Slope	2.76	82.17[c]
	(18.05)	(36.99)
Soil permeability	10.84[b]	20.08[b]
	(2.71)	(3.76)
Section temperature	−82.01[c]	−204.16[c]
	(38.00)	(99.98)
Annual temperature	43.48	84.89[b]
	(37.44)	(20.86)
Fuel price	31.92	−7.39
	(32.02)	(14.66)
Citrus/drip area	5.18[b]	2.90[b]
	(0.43)	(0.92)
Citrus/gravity area	9.52[b]	6.32
	(1.39)	(21.82)
Grape/drip area	4.10[b]	2.40[b]
	(0.52)	(1.02)
Grape/gravity area	6.04[b]	3.08
	(0.55)	(2.65)
Deciduous/drip area	7.24[b]	4.41
	(0.71)	(2.40)
Deciduous/gravity area	8.69[b]	12.61[b]
	(0.92)	(2.28)
Deciduous/sprinkler area	7.64[b]	4.32
	(1.05)	(11.68)
Truck/sprinkler area	4.07[b]	2.74
	(0.46)	(6.10)
Truck/gravity area	6.32[b]	4.19[b]
	(1.11)	(0.89)
Field/sprinkler area	6.20[b]	6.07[b]
	(0.46)	(1.39)
Constant	1438.4	4662.5
	(1968.1)	(3576.1)
R-sq	0.427	

[a]Dependent variable is total water use at each section, measured in thousands of cubic meters. Numbers in parentheses are standard errors, with the robust IV standard errors calculated using bootstrapping.
[b]Significance at the 99th percentile.
[c]Significance at the 95th percentile.

pump groundwater, so we know that surface water is their marginal source for irrigation. For this paper, we use only those producers in the surface water service area, as their water use is metered and hence measurable. Because of this, the area covered by our data is reduced by the amount of land under groundwater irrigation, but still covers almost 22,000 hectares (55,000 acres).

[24] One other reason that AEWSD is well suited to measure water demand is that the water district practices groundwater banking for its customers. During wet years when the district receives a large allocation of surface water, it uses spreading fields to store some of that water underground. During dry years when the district receives a small allocation, it pumps the reserve water to deliver to its surface water users. Because of this practice, the producers in AEWSD are not subject to the same stochastic variation in water availability as those producers in other regions of California.

[25] The data set includes an 8-year panel of 117 sections (predetermined, time-invariant blocks of land) in AEWSD, which covers the period from 1994 until 2001. Also important is the fact that in 1995, the District enacted a major water rate reform that facilitates identification of the demand function. Like many water authorities, AEWSD prices water according to a two-part tariff. Agricultural producers pay a fixed per hectare fee for access to water, and this fee is paid if the land is left fallow or in production. There is an additional variable fee which is paid per thousand cubic meters of water. In 1995, AEWSD decreased the fixed component and increased the variable one; a change intended to encourage water conservation by increasing its marginal price. By comparing water use before and after the rate reform, we can capture the effects of the price change controlling for factors such as environmental conditions and changes in output prices.

[26] Table 2 gives historical water prices to surface water users during the study period. Before 1995, AEWSD assessed a fixed per hectare fee of $340.8, and a variable charge of $36.7 per thousand cubic meters of water delivered. In 1995, the District reduced the fixed fee by over 30 percent to $235.0, and increased the variable fee by over 40 percent to $53.0. In 1999, the variable charge decreased because AEWSD found it was overcollecting revenue after the 1995 price change, as water districts in California operate on a revenue-neutral basis.

[27] The environmental variables used are chosen to reflect soil and topography characteristics relevant to farming and irrigation. These variables (slope, permeability, number of frost-free days per year, and average temperature) are long-run averages and do not change over time, but do vary over section. These variables were collected by the Kern County Natural Resource Conservation Service, and are described in more detail by *Green et al.* [1996]. Yearly temperature averages for the area were obtained from the Western Regional Climate Center. The use of the two temperature variables addresses two sources of variation in temperatures: cross-sectional variation among microclimates within the district and variation across years.

[28] Table 3 shows the total area in each land allocation choice during the study period, with the inclusion of fallow as a possible land use. In our empirical analysis, we consider only certain crop and irrigation technology combinations, as some combinations are not observed in our data. For example, truck crops grown under drip irrigation, while technically feasible, are not observed in our sample. The pairs we consider are citrus crops with drip or gravity, grape crops with drip or gravity, deciduous crops with drip, gravity, or sprinkler, truck crops with gravity or sprinkler, and field crops with sprinkler. The main citrus crop in the region is oranges; deciduous crops include mostly almonds, along with some peaches and apples. Truck crops include potatoes, carrots, and onions, while field crops include cotton and some hay. We use output prices as one set of information which identifies crop choice. Most of these data were obtained from the annual Kern County Agricultural Commissioner's Crop Report, with the exception of the price of carrots, which was from the U.S. Department of Agriculture. As we do not have farmer or section level output prices, there may be minor discrepancies between these data and the actual price received (due to different types of contracts or relationships with processors). However, these prices on average reflect the relative profitability of different crops.

Table 6. Tobit Estimation Results for Perennial Crops[a]

	Citrus Drip	Citrus Gravity	Grape Drip	Grape Gravity	Deciduous Drip	Deciduous Sprinkler	Deciduous Gravity
Water price	0.08	0.44	−0.38	0.39	0.12	−0.64	0.22
	(0.16)	(0.49)	(0.22)	(0.23)	(0.39)	(0.38)	(0.40)
Farm wage	0.47	−37.92	15.99[b]	−21.74[c]	−2.23	−0.73	2.67
	(5.30)	(21.01)	(6.88)	(7.94)	(11.99)	(13.15)	(13.9)
Annual temperature	−2.30	−20.23	8.74	−11.51	−8.33	−4.15	10.92
	(4.17)	(15.08)	(5.49)	(6.12)	(9.40)	(10.56)	(10.84)
Slope	2.55[c]	3.28	1.66	−5.06[b]	1.76	−1.61	−11.55[b]
	(0.85)	(3.12)	(1.24)	(2.19)	(2.03)	(3.14)	(5.36)
Soil permeability	−1.97	−48.90	9.08	3.62	31.18[b]	41.47[b]	−26.86
	(5.91)	(36.51)	(7.87)	(9.65)	(14.80)	(16.26)	(24.19)
Frost-free days	−0.98	−3.83	2.70	4.88[b]	3.68	0.90	12.10[b]
	(0.78)	(2.85)	(1.60)	(2.33)	(2.68)	(3.80)	(5.75)
Section temperature	3.54	28.84	−11.37	−18.88	−30.20[b]	36.24	−3.32
	(4.74)	(17.04)	(7.52)	(9.92)	(13.46)	(19.85)	(23.27)
Fuel price	4.28	86.48	−54.85[b]	73.10[c]	27.73	−8.38	−13.00
	(16.40)	(62.20)	(21.45)	(24.50)	(36.38)	(41.93)	(44.13)
Lagged perennial price index	1.18	4.60	−2.43	3.28	3.60	−0.85	−2.15
	(1.38)	(4.15)	(1.83)	(1.98)	(3.20)	(3.25)	(3.43)
Lagged annual price index	−0.88	−10.03	6.50[b]	−10.43[c]	−4.70	−5.38	5.70
	(2.35)	(7.60)	(3.08)	(3.50)	(5.40)	(6.00)	(5.93)
Citrus/drip lagged area	1.13[c]	−0.10	0.04	−0.02	0.17[c]	−0.37[c]	−0.00
	(0.02)	(0.10)	(0.03)	(0.04)	(0.05)	(0.13)	(0.09)
Citrus/gravity lagged area	0.05	1.95[c]	−0.07	0.28[b]	0.11	−0.23	0.74[c]
	(0.08)	(0.19)	(0.13)	(0.11)	(0.19)	(0.33)	(0.23)
Grape/drip lagged area	0.03	0.09	1.32[c]	0.07	0.29[c]	0.04	−0.06
	(0.03)	(0.09)	(0.04)	(0.05)	(0.06)	(0.07)	(0.10)
Grape/gravity lagged area	−0.004	−0.54[b]	0.11[c]	1.23[c]	0.18[c]	−0.46[c]	0.16[b]
	(0.03)	(0.26)	(0.04)	(0.04)	(0.07)	(0.16)	(0.06)
Deciduous/drip lagged area	0.02	−0.13	0.02	0.01	1.42[c]	0.04	0.33[c]
	(0.04)	(0.25)	(0.05)	(0.06)	(0.07)	(0.09)	(0.07)
Deciduous/sprinkler lagged Area	−0.13	−0.15	0.03	−0.13	0.54[c]	1.28[c]	0.02
	(0.08)	(0.24)	(0.07)	(0.11)	(0.09)	(0.09)	(0.13)
Deciduous/gravity lagged area	−0.11	0.36[c]	0.06	0.06	0.28[c]	0.35[c]	1.50[c]
	(0.07)	(0.12)	(0.07)	(0.06)	(0.11)	(0.10)	(0.10)
Truck/sprinkler lagged Area	0.03	0.01	−0.10[b]	−0.10[b]	0.15[b]	0.04	−0.09
	(0.03)	(0.07)	(0.04)	(0.04)	(0.06)	(0.06)	(0.07)
Truck/gravity lagged area	−0.11	−0.35	−0.11	−0.43[b]	0.01	−0.31	0.01
	(0.08)	(0.55)	(0.10)	(0.17)	(0.17)	(0.20)	(0.14)
Field/sprinkler lagged area	−0.12[c]	−0.17	0.07	−0.09[b]	0.03	0.14[b]	−0.07
	(0.04)	(0.15)	(0.04)	(0.04)	(0.07)	(0.06)	(0.08)
Constant	46.4	1314.6	−886.6	1692.7[b]	1469.6	−1153.2	−2450.4
	(492.3)	(1728.9)	(655.7)	(752.3)	(1134.4)	(1385.7)	(1478.6)
Pseudo R-Sq.	0.26	0.31	0.21	0.22	0.17	0.18	0.20
Censored obs.	598	891	658	698	790	838	831
Uncensored obs.	338	45	278	238	146	98	105

[a]Dependent variables are the number of hectares in each crop and technology pair. Numbers in parentheses are standard errors.
[b]Significance at the 95th percentile.
[c]Significance at the 99th percentile.

[29] Table 4 includes summary statistics on all of the variables used in the land allocation and water demand estimations. While there are a small number of observations with close to zero water use (the minimum level observed is one thousand cubic meters), less than one percent of the observations are under 123 thousand cubic meters. The wage rate for field-level agricultural workers is based on California data collected by the USDA through the National Agricultural Statistics Service, and the price for fuel is based on California data collected by the Department of Energy.

4. Results

4.1. Water Demand Results

[30] The results of the water demand estimation are in Table 5. For comparison, we present the results of the OLS estimation and the IV estimation with bootstrapped standard errors. The results are very similar across econometric specifications. We find that the coefficient on water price is negative in both circumstances, but the IV estimation allows better identification of the importance of that variable and thus the significance is greater in the IV estimation. This finding demonstrates that marginal price can influence farm water demand, even controlling for other factors such as output choice and capital investments in production technology. The significance of water price in this equation suggests that better management alone can result in significant water conservation, even in the short run. The coefficients on the estimated land area levels are more significant in the OLS estimation, reflecting the fact that the instruments for these variables are not perfect, although the results in

Table 7. Tobit Estimation Results for Annual Crops[a]

	Truck Sprinkler	Truck Gravity	Field Sprinkler
Water Price	−5.30[b]	−7.10[c]	−4.33[c]
	(1.90)	(3.53)	(2.00)
Farm Wage	150.10[c]	−435.33[b]	13.53
	(66.55)	(126.93)	(67.78)
Annual temperature	73.82[b]	−153.28[b]	25.17
	(16.28)	(35.50)	(16.49)
Slope	−12.63	−32.80	−47.03[b]
	(13.98)	(39.78)	(16.13)
Soil permeability	14.73	−152.72[b]	32.26[c]
	(13.27)	(43.56)	(13.72)
Frost-free days	0.13	206.08	8.18[b]
	(2.25)	(162.65)	(2.90)
Section temperature	−2.21	−37.81	−58.64[b]
	(12.64)	(40.85)	(14.62)
Fuel price	−95.35[b]	227.15[b]	−23.78
	(33.45)	(63.73)	(33.90)
Lagged annual price index	25.98[b]	−46.55[b]	7.28
	(4.63)	(11.68)	(4.73)
Lagged perennial price index	−10.78[b]	8.18	−1.68
	(2.70)	(4.83)	(2.75)
Citrus/drip lagged area	−0.25[b]		−0.34[b]
	(0.06)		(0.08)
Citrus/gravity lagged area	0.03		−0.73[c]
	(0.17)		(0.28)
Grape/drip lagged area	−0.01		0.07
	(0.06)		(0.06)
Grape/gravity lagged area	−0.34[b]		−0.31[b]
	(0.08)		(0.07)
Deciduous/drip lagged area	0.13		0.06
	(0.07)		(0.07)
Deciduous/sprinkler lagged area	−0.01		0.04
	(0.11)		(0.10)
Deciduous/gravity lagged area	0.10		0.10
	(0.10)		(0.10)
Truck/sprinkler lagged area	0.85[b]	0.39[b]	0.25[b]
	(0.04)	(0.08)	(0.05)
Truck/gravity lagged area	0.55[b]	1.08[b]	0.32[b]
	(0.10)	(0.13)	(0.10)
Field/sprinkler lagged area	0.32[b]	0.28[b]	0.87[b]
	(0.05)	(0.08)	(0.05)
Constant	−4041.1[b]	−11,758.7	454.3
	(1036.3)	(17,620.1)	(1064.8)
Pseudo R-Sq.	0.10	0.16	0.11
Censored obs.	513	843	542
Uncensored obs.	423	93	394

[a]Dependent variables are the number of hectares in each crop and technology pair. Numbers in parentheses are standard errors.
[b]Significance at the 99th percentile.
[c]Significance at the 95th percentile.

the IV estimation are of greater significance for the variables with a greater number of nonzero observations.

4.2. Land Allocation Results

[31] The results of the Tobit estimations are presented in Tables 6 and 7. We find that the coefficient on lagged area in the same crop and technology is always positive and significant. This shows that there is a cost of adjusting land allocation each period. We also find that this coefficient is larger in magnitude with permanent crops, reflecting the greater cost of moving land out of these crops, and the fact that the decision to invest in these crops should be seen as long-term investment instead of an annual choice. We also estimate the effect on changes in land allocation between years instead of the level of area. We find negative coefficients in the lagged area of annual crops using this measure, evidence which supports the observations of crop rotation between field and truck crops between years.

[32] Another interesting result comes from the coefficient on the water price variable. This coefficient is insignificant with land allocations in perennial crops, reflecting the relatively high cost of adjustment and large capital investment required to grow these crops. However, the coefficient is negative and significant in all of the annual crops, reflecting the greater amount of land in fallow with higher water prices. This result supports the hypothesis that land allocation is altered at both the extensive and the intensive margins.

4.3. Direct and Indirect Water Price Elasticity

[33] One benefit of the estimation strategy we use is that the microeconomic response to changes in water price can be decomposed into direct and indirect effects, where the latter include changes in capital investment and land allocation. We define β_3 as the $J \times 1$ vector of estimated coefficients on the water price variable, $[\beta_{31}\beta_{32}\ldots\beta_{3J}]'$. Using the notation from equations (2) and (1), we calculate the following formula for the change in water use with respect to the price of water:

$$\frac{\partial W_{it}^D}{\partial p_{wt}} = \gamma_4 + \gamma_3'\beta_3\Phi\left(\frac{\beta' X_{ijt}}{\sigma_j}\right). \tag{6}$$

The first term in equation (6) measures the direct effect of improved water management, while the second term refers to the indirect effects of changes in land allocation, where we use the marginal effects from the Tobit estimations. As the Tobit estimations are nonlinear by design, the marginal effects differ from the coefficients in the land allocation estimations. Converting the marginal effect into an elasticity, measured at mean values, gives the following:

$$\begin{aligned} \epsilon_p &= \frac{\partial \overline{W}^D}{\partial \overline{p_w}} \frac{\overline{p_w}}{\overline{W}^D} \\ &= \gamma_4 \frac{\overline{p_w}}{\overline{W}^D} + \gamma_3'\beta_3\Phi\left(\frac{\beta' X_{ijt}}{\sigma_j}\right)\frac{\overline{p_w}}{\overline{W}^D} \end{aligned} \tag{7}$$

[34] The first term in equation (7) refers to the direct price elasticity, while the second term refers to the indirect price elasticity. Table 8 presents the estimated demand elasticities from each econometric specification. The direct elasticities are all negative and significantly different from zero at the average values in our sample, providing evidence of improved water management and conservation at higher water prices. The indirect elasticity is also negative, implying that a change in the price of water induces water-conserving changes in crop and technology choices. It should also be noted that the indirect effects of water price are of a similar magnitude to the direct effects. This pattern is explained by the fact that, while the price of water has been shown to be a significant determinant of adoption of conservation technology in agriculture, it is by no means the only determinant [*Green et al.*, 1996]. Other factors such as weed control, a desire to save on labor costs, or a need to apply fertilizers precisely through the irrigation system can all spur investment in precision irrigation systems. Similarly, in most cases the price of water has been shown to have only a relatively small influence on crop choice since the price of water is often a small share of the cost of production,

Table 8. Estimated Direct and Indirect Water Demand Elasticities[a]

	Direct Elasticity	Indirect Elasticity	Total Elasticity
OLS Estimation	-0.184^{b}	–	-0.184^{b}
	(0.087)	–	(0.087)
Heteroskedastic IV (with AR(1))	-0.415^{c}	-0.372^{c}	-0.787^{c}
	(0.084)	(0.107)	(0.132)

[a]Numbers in parentheses are the bootstrapped standard errors of the estimates.
[b]Significance at the 95th percentile.
[c]Significance at the 99th percentile.

although certain regions and crops have shown an elastic response to changes in the price of water [*Moore et al.*, 1994].

[35] The calculated total own-price elasticity of water use has a point estimate of −0.787. This finding implies that agricultural water demand is somewhat more elastic with respect to the price of water than indicated by previous studies. Accordingly, one implication of our research is that water rate changes can have a larger effect on water allocation than previously assumed. It is also worth noting that our panel only includes 7 years of data after the major rate change. Given the durability of capital investments in irrigation systems, which can have a useful life of ten years or more, and plant stock, which can last up to forty years for some trees and vines, the indirect effects may be larger when measured over a longer time period.

5. Conclusion

[36] This paper develops and estimates a model of agricultural water demand based on the role of water in the farm production function. It then presents estimates of the parameters of the model using a unique panel data set from California's San Joaquin Valley. The data we have collected for this analysis is of a level of quality and completeness which is rare in the literature on agricultural water demand. One objective of our analysis is to measure the price elasticity of farm water use, as it provides important information about the effectiveness of price reforms to manage water demand. Our results support the hypotheses that farmers respond in two ways to an increase in the marginal price of water, both by reducing their water applications and altering their land allocation. We also find that under moderate prices, agricultural water demand is more elastic than shown in previous work, a result which has important implications for differences in the optimal design of policies directed at agricultural users of water. Beginning with the seminal work of *Fisher and Kayesn* [1962], work in the electricity demand literature has found that the relationship between price elasticity of demand and price has an inverted U shape, where demand is inelastic with low and high prices but more elastic with moderate prices.

[37] These predicted values of land allocation and irrigation technology choice are used as instruments in the water demand estimation. The direct own-price elasticity, or the component due to better management of water resources, is in the range of −0.18 to −0.42, while the estimated indirect component of the total price elasticity (due to land reallocation and increased levels of fallow land) is −0.37. Of this total elasticity, the indirect effects of water price on output and technology choices account for roughly 47 percent of the total, while direct effects make up the balance. This finding suggests that more active management has a large influence on water use, although the indirect effects of land use change are also significant, and must be considered in the determination of long-run water demand.

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