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Estimating Producer's Surplus with the Censored Regression Model: An Application to Producers Affected by Columbia River Basin Salmon Recovery

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Application of the tobit model to estimate economic welfare is transferred from the consumer side to the producer side. Supply functions are estimated for multioutput irrigators in the Pacific Northwest. Empirical procedures are then developed for computing expected producer's surplus from the output supply functions. Confidence intervals for the surplus measures are generated using the Krinsky-Robb method. An experiment predicts decreases in surplus given increases in water pumping cost. The experiment replicates possible increases in hydroelectric prices due to the salmon recovery program in the Columbia-Snake River Basin. Output substitution explains producers' ability to mitigate the effect of the price increases on producer's surplus.

Key words: Endangered Species Act, multioutput supply, Pacific Northwest, producer's surplus, salmon, tobit regression, water price

Introduction

Recently developed tools of applied benefit-cost analysis emphasize measuring the unmarketed benefits of public goods. The use of limited dependent variable regression models with the travel cost method (e.g., Bockstael et al.; Hellerstein) and the dichotomous choice approach to the contingent valuation method (Bishop and Heberlein; Arrow et al.) improve the quality of estimates of consumer demand for environmental goods and services. For the travel cost method in particular, a censored regression model may produce econometrically consistent parameter estimates of recreation demand functions and, as well, may generate estimates of consumer's surplus that differ greatly from those generated with the ordinary least squares (OLS) regression model (Bockstael et al.).

These same techniques can be applied to improve estimates of changes in producer's surplus from environmental programs or policies.[1] For example, a censored regression

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[1] On the producer side, dichotomous choice contingent valuation was recently applied to estimate producers' willingness to accept incentive payments to adopt best management practices (BMPs) under the U.S. Department of Agriculture's (USDA's) Water Quality Incentive Program (Cooper and Keim).

model, or the tobit model, can be fruitfully applied to estimate producer's surplus under certain behavioral conditions. Consider the following example of estimating crop supply functions of multioutput producers. Two conditions combine to make a censored model appropriate. First, producers choose from a set of crops commonly grown in a region, implying that producers operate with a common multioutput technology. Second, every producer does not grow every crop, i.e., producers can be segregated into those at a threshold of zero and those above the threshold in production of a given crop. The ability to identify an agent as either at or above a threshold in any economic activity implies that the censored regression model will be a superior estimator (Maddala). With data available on individual multioutput producers, the censored regression model offers improvements over linear regression models, both for estimating crop supply functions and calculating producer's surplus with these functions.

We develop an approach for estimating producer's surplus for the multioutput producer. Two distinctions arise when estimating surplus on the producer side relative to the consumer side. The first concerns the number of markets that are analyzed to estimate economic welfare. In the case of the consumer, an individual's recreational demand and consumer's surplus typically is isolated from demand for other goods by assuming a weakly separable utility function (Phlips). By contrast, in the case of the multioutput producer, we calculate producer's surplus for each crop and then sum across crops as a measure of an individual's total producer's surplus. We later describe the assumption on production technology that permits this. The second distinction relates to selecting a choke price.[2] An important issue in applying the censored regression model to compute consumer's surplus is that the analyst must choose a consumer's choke price; yet this choice markedly affects estimates of surplus (Hellerstein). As we describe, choosing a producer's choke price for a supply function when computing producer's surplus raises similar, although distinct, issues.

The empirical application involves estimation of expected producer's surplus for irrigators in the Pacific Northwest. The tobit estimator is used to estimate crop supply functions. Expected producer's surplus is then computed from the unconditional expected supply functions. In addition, the Krinsky-Robb method (Krinsky and Robb) is used to generate confidence intervals for these surplus measures. We also conduct an experiment of predicting changes in expected producer's surplus given a change in water prices (measured as pumping cost for water). The experiment relates directly to consequences of the salmon recovery program in the Columbia-Snake River Basin under the Endangered Species Act (Northwest Power Planning Council; U.S. Department of Commerce 1995, 2000). Operations of several federal hydroelectric facilities in the basin may be altered to improve conditions for salmon survival. These facilities generate much of the electricity for water pumping in the Northwest. The experiment is designed to replicate the range and geographic pattern of possible increases in hydroelectricity prices—and thus pumping costs—within the region [Columbia River System Operation Review (SOR) Interagency Team 1994b].

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[2] For the consumer, "choke price" is the price at which quantity demanded equals zero.

Expected Producer's Surplus in the Censored Linear Model

We apply the basic concept of calculating producer's surplus[3] from output supply functions (Just, Hueth, and Schmitz, chapter 4) to the case of a multioutput producer. A competitive firm's supply curve coincides with its marginal cost curve when marginal cost is upward sloping. Thus, by estimating supply functions for the multioutput producer, one measure of the firm's profitability can be computed without more basic information on its underlying technology or cost structure.

The tobit regression model handles the threshold/nonthreshold behavior that characterizes multioutput choices. This behavior is commonly observed with agricultural production: individual data from the Pacific Northwest (described later) reveal that many multicrop producers choose to grow only a subset of a common set of five field crops. With the tobit model, producers with zero supply of a crop remain in the econometric analysis to avoid the problem of inconsistent parameter estimates (Maddala).[4] Computation of the expected value of consumer's surplus from demand functions estimated with the tobit model raises issues not posed in application of the OLS model (or other linear regression models). Previous research on outdoor recreation has developed techniques to address these issues (Bockstael et al.; Hellerstein). Following this line of research, we compute the expected value of producer's surplus (expected producer's surplus) using crop supply functions estimated with the tobit regression model.

Again, two distinctions emerge when computing expected producer's surplus, rather than expected consumer's surplus, with this approach. One distinction involves computation of surplus across markets in which the agent is active. By assuming weak separability of utility functions, evaluation of a consumer's recreational demand function—without analysis of demand for other goods—generates a complete measure of consumer's surplus from recreation. In the case of the multioutput producer, we follow three steps to obtain a complete measure of producer's surplus: (*a*) estimate individual crop supply functions for a set of crops, (*b*) compute expected producer's surplus for each crop, and (*c*) sum over the crops to generate multioutput producer's surplus. Here the traditional assumption of input nonjointness is adopted (Chambers and Just; Just, Zilberman, and Hochman). Input nonjointness implies that the multioutput profit (cost) function is the sum of output-specific profit (cost) functions (Chambers, p. 293). It ensures that, for an individual producer, crop-level estimates of producer's surplus can simply be summed to generate a multicrop measure.

A second distinction on the producer side involves selection of a choke price, that is, the price at which output supply equals zero. When computing expected consumer's surplus from a linear demand function that is censored at zero, the analyst must choose a choke price (from a reasonable set of alternatives) when integrating under the expected value of the demand function between observed price and choke price to obtain the surplus measure (Hellerstein). If censoring were ignored (say, the expected value of demand

[3] Producer's surplus is equivalent to quasi-rent (Just, Hueth, and Schmitz, p. 54). Algebraically, it is equal to total revenue minus total variable cost. Graphically, it is the area above the supply curve and below the price line of a firm or industry.

[4] Multioutput production raises an econometric issue of efficiency in addition to consistency. Efficiency likely requires estimation of a system of supply equations. However, estimating tobit regressions in a system framework is computationally difficult with current techniques.

is set equal to the nonstochastic component of a linear function), a choke price can easily be computed. However, when censoring is properly accounted for, the expected value of demand becomes a nonlinear function dependent on the assumed distribution of the stochastic component. In contrast to the case of linear expected value, this nonlinear function approaches the price axis asymptotically. The choice of choke price can greatly influence the results. Hellerstein (p. 88) reported estimates of aggregate consumer's surplus that deviated from true aggregate surplus between 10% and 67% depending on the level of choke price. We address the topic of the supply-side choke price after first introducing the model.

Model Elements

Crop supply functions for the multioutput producer follow directly from standard duality results. We apply the same model of multicrop irrigated agricultural production as developed in Moore, Gollehon, and Carey. The supply functions for a given producer are specified as:

$$y_i = y_i(\mathbf{p}, \mathbf{w}, N), \quad i = 1, \ldots, m, \tag{1}$$

where y_i is the output of crop i ($i = 1, \ldots, m$); $\mathbf{p}$ is a vector of crop prices; $\mathbf{w}$ is a vector of variable input prices; and N is the farm-level land endowment.[5] The empirical specification of the supply functions is linear in the independent variables. Linearity follows from application of the normalized quadratic functional form for the crop-specific profit functions (Moore, Gollehon, and Carey, p. 861).

For a particular crop, some producers choose to grow the crop while others choose not to grow. Output data of this form generate a censored dependent variable on supply (Maddala, pp. 149–51). Application of the tobit model to a crop assumes that observed supply follows the rule:

$$y = \begin{cases} \mathbf{X}\beta + \varepsilon & \text{if } RHS > 0, \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

where $\mathbf{X}\beta$ is the inner product of independent variables and coefficients and ε is the error term, assumed independently and normally distributed, with mean zero and variance σ^2. Unconditional expected supply of a crop (the average quantity produced by a random individual) equals:

$$E[y] = \Phi * \mathbf{X}\beta + \sigma\phi, \tag{3}$$

where σ is the standard deviation of ε, and Φ and ϕ are, respectively, the distribution function and density function of the standard normal, both evaluated at $(\mathbf{X}\beta/\sigma)$ [equation (6.37) in Maddala]. Expected supply with censoring contrasts with the familiar expected supply from ordinary least squares, $E[y] = \mathbf{X}\beta$.

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[5] This specification of the supply functions uses the result that $y_i(\mathbf{p}, \mathbf{w}, N) = y_i(p_i, \mathbf{w}, n_i)$ (Chambers and Just, p. 982). In this relationship, crop-specific land allocations (n_i) sum to total acreage on the farm (N).

We estimate *expected* producer's surplus,[6] rather than producer's surplus, because of the water-price experiment conducted later.[7] Following Hellerstein's (pp. 85–86) development of expected consumer's surplus, expected producer's surplus from crop i for an individual producer facing observed output price P^i_{obs} and choke price P^i_c is written as:

$$(4) \qquad E[PS] = \int_{P^i_c}^{P^i_{obs}} y_i(\mathbf{p}, \mathbf{w}, N|\varepsilon)\, dp_i, \quad i = 1, \ldots, m.$$

Using the notation of $\mathbf{X}\beta$, expected producer's surplus in the tobit model is:

$$(5) \qquad E[PS] = \int_{P^i_c}^{P^i_{obs}} (\Phi * \mathbf{X}\beta + \sigma\phi)_i\, dp_i, \quad i = 1, \ldots, m.$$

This is the formula applied empirically.

We now turn to defining the choke price to be applied in calculating $E[PS]$. In the case of the producer, an upward-sloping linear supply function intersects the price axis (although the intersection may occur where price is negative). However, when censoring is accounted for and an unconditional expected value is used, the supply function approaches the price axis asymptotically in the range of negative price. Unconditional expected supply is always positive, even when price is negative (figure 1).

Three methods of choosing a choke price seem sensible given this context. First, the horizontal axis, representing the line at which price equals zero (labeled $P_c = 0$ in figure 1), establishes a lower bound for a choke price. This rule precludes a producer from supplying output at a negative price. As the lowest choke price, $P_c = 0$ establishes the upper bound on $E[PS]$ (the area $A+B+C+D$ in figure 1). Further, $P_c = 0$ has the attractive feature of placing a ceiling on $E[PS]$ in an objective manner, without resorting to the analyst's judgment. This contrasts distinctly with the case of expected consumer's surplus, which has no upper bound in the censored linear model unless the analyst imposes a choke price.

Second, one can turn to the interpretation of the supply function as equivalent to the short-run marginal cost function. With the supply functions estimated here, the marginal cost function is everywhere upward sloping. On intuitive grounds, however, it can be argued that the short-run marginal cost function is constant at relatively low levels of output, then begins to increase (Varian, p. 25): prior to reaching capacity constraints on fixed inputs, marginal cost is constant because of a region of constant returns to scale; marginal cost increases upon reaching the capacity constraints.

The choke price for this regime would correspond to the flat portion of the marginal cost function; it is labeled $P_c = CMCA$ to represent the "constant marginal cost assumption." As depicted in figure 1, $E[PS]$ equals $A+B+C$ for this regime.

In the empirical study, econometric estimation of a kinked supply function—to represent the marginal cost function described above—is inhibited by the range of the data on production and output price. Instead, approximations of constant marginal cost are

[6] In particular, we compute unconditional expected producer's surplus. "Unconditional" assumes that information does not exist on whether a producer chooses to grow a particular crop. In contrast, conditional expected producer's surplus refers to producers who are known to be participants. Since conditional expected surplus assumes production is strictly positive, it always meets or exceeds unconditional unexpected producer's surplus.

[7] Bockstael et al. (p. 44) emphasize that the appropriate comparison when evaluating an experimental change in an exogenous variable is to compare expected surplus before and after the change. This is done for consistency in evaluation, relative to the alternative of comparing actual surplus before the change to expected surplus after the change.

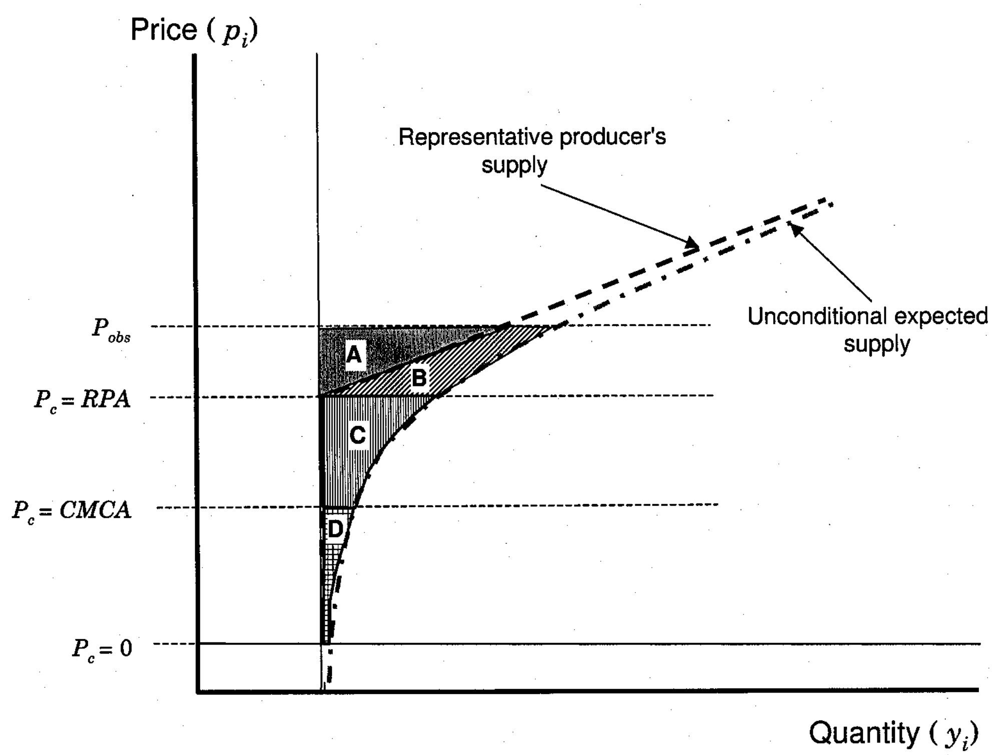


Figure 1. Expected producer's surplus under alternative choke-price regimes

developed from crop budget data from Idaho, Oregon, and Washington. We emphasize that, while $P_c = CMCA$ has conceptual merit as a choke price, our application is imperfect because of data limitations in the econometric application.

Third, following the literature on consumer's surplus, we use the choke price of the "representative" producer;[8] this is labeled $P_c = RPA$ in figure 1 for the "representative producer assumption." The regime $P_c = RPA$ is identical in concept to Hellerstein's (p. 87) $TOB\_\int\mu$ method. This choke price is computed as if the price intercept for a non-censored, nonstochastic linear supply function were being calculated (figure 1). That is, if the supply function equals

$$y = k + \beta_1 p, \tag{6}$$

where β_1 is the estimated coefficient on the own-crop price variable and k equals the sum of the product of estimated coefficients and independent variables for every variable but the own-crop price, then the choke price equals $-k/\beta_1$. (Note that β_1 and the estimated coefficients underlying k are derived from the tobit model.) Measurement of $E[PS]$ equals $A + B$ in figure 1.

Two points are relevant. First, the figure's depiction of $E[PS]$ as larger under $P_c = CMCA$ relative to $P_c = RPA$ is arbitrary; in principle, the reverse could be true. Second, none of

[8] The "representative" producer, identified as the producer with $\varepsilon = 0$, can be described as the median producer: ceteris paribus, half of the producers will produce more and half will produce less than the representative producer.

the three regimes for setting choke price is conceptually superior to the others. In combination, though, they define a reasonable first approach to apply in estimating expected producer's surplus with the censored regression model.

Empirical Estimation

Data and Variables

Crop-level and farm-level producer's surplus are estimated from supply functions for five irrigated field crops: alfalfa hay, barley, corn for grain, dry beans, and wheat. This is a common set of crops grown in the Northwest (Idaho, Oregon, and Washington). Farms included in the sample grow at least two of the five common field crops and do not grow specialty crops (orchards, berries, and vegetables).

The primary data are cross-sectional data from the 1984 and 1988 Farm and Ranch Irrigation Survey (FRIS), a survey of operators of irrigated farms (U.S. Department of Commerce 1986, 1990). The survey includes questions on output, cropland use, and irrigation water use by crop, as well as questions on irrigation technology, water sources, and water management practices. Several variables are formed from these data, and are described in table 1. (For interested readers, additional description of the data and variables is provided in earlier research by Moore, Gollehon, and Carey).

Producers in the sample irrigate with water that requires pumping, either groundwater or surface water that requires lifting, conveyance, and/or pressurization. Groundwater is assumed to be the marginal source when both sources are used. An engineering formula translates pumping lift and pressure into marginal pumping cost in dollars per acre-foot;[9] this cost serves as the measure of water price (as in Caswell and Zilberman; Moore, Gollehon, and Carey).

Secondary data sources are used to create variables to merge with the FRIS-based variables. Three categories of variables are defined: output and input prices, climate, and soil quality. Crop price variables are constructed as expected 1984 and 1988 prices, based on econometric-based predictions using state-level time-series data from the USDA. Variable input prices are current-year prices. They include farm-level water prices computed from FRIS data, and state-level wages and regional-level bulk-purchased gasoline prices from the USDA. Two climate variables represent expected weather conditions for a season: county-level growing season precipitation and cooling degree-days, both based on 30-year averages from National Oceanic and Atmospheric Administration (NOAA) weather stations. Soil variables represent cropland quality, including soil texture and land class. They are average county cropland values from the USDA/Natural Resource Conservation Service's 1982 National Resources Inventory.

Representative farm crop budgets from various states' Cooperative Extension Services are used to compute average variable cost on a dollar per unit output basis (Bolz, Rimbey,

[9] To compute a water price for each farm observation, energy cost for each fuel source is computed from farm-level FRIS data on groundwater pumping depth and pumping pressure by applying the formula (Gilley and Supalla, p. 1785): $C = P*(1.3716/0.885)*(L + 2.31*PSI)$, where C = pumping cost in \$/acre-foot, P = electric price in \$/kwh, L = distance in feet that water is lifted, PSI = pumping pressure in pounds per square inch, 0.885 is a fuel-efficiency adjustment for electricity, and 1.3716 and 2.31 are constants. For farms with groundwater, pumping lift is reported on the FRIS as depth to water table. For farms pumping surface water, pumping lift is computed from FRIS data on on-farm pumping costs, electricity prices, and pressure needs of the water delivery system. Variation in pumping lift and pressure translate into variation in the water price variable.

Table 1. Descriptive Information for Selected Variables

Variable	Unit	Pacific NW	State: ID	OR	WA
FARM-LEVEL VARIABLES:					
Number of Farms		529	252	117	160
Farm Area	acres				
Mean		1,297	1,461	1,156	1,140
Standard Deviation		1,445	1,337	1,383	1,626
Water Applied	acre-feet				
Mean		2,281	2,456	2,266	2,019
Standard Deviation		3,002	2,715	3,581	2,970
Base Normalized Water Price	\$/acre-foot/NP [a]				
Mean		17.18	18.82	14.04	16.91
Standard Deviation		9.30	9.23	6.66	10.44
Cooling Degree-Days	degree-days				
Mean		3,806	3,615	3,499	4,331
Standard Deviation		826	766	953	524
Growing Season Precipitation	inches				
Mean		4.45	4.93	4.23	3.88
Standard Deviation		1.43	0.83	2.41	0.87
Normalized Wage Rates	\$/hour/NP				
Mean		4.03	3.67	4.22	4.46
Standard Deviation		0.74	0.68	0.37	0.75
Bulk Gasoline [b]	\$/gallon				
Mean		1.05	1.07	1.02	1.05
Standard Deviation		0.11	0.10	0.10	0.13
Water Source					
Ground water only	% of farms	44	48	29	48
Surface and ground water	% of farms	41	43	56	26
Surface water only	% of farms	15	9	15	26
Pressure Irrig. Technologies Avail.	% of farms	95	92	95	99
Water Mgmt. Method on Farm					
Advanced methods used	% of farms	25	29	26	19
Fixed-time methods used	% of farms	22	19	25	26
CROP-LEVEL VARIABLES (means only):					
Normalized Output Prices					
Alfalfa	\$/ton/NP	61.05	55.52	70.65	60.76
Barley	\$/bushel/NP	2.25	2.32	2.23	2.06
Corn	\$/bushel/NP	2.67	2.58	3.07	2.61
Dry Beans	\$/cwt/NP	15.71	15.67	15.81	15.75
Wheat	\$/bushel/NP	2.95	2.79	3.21	3.02
Mean Acres [c]					
Alfalfa	acres/farm	319	374	336	211
Barley	acres/farm	322	387	255	189
Corn	acres/farm	359	119	539	473
Dry Beans	acres/farm	212	262	180	130
Wheat	acres/farm	483	490	231	626

(continued)

Table 1. Continued

Variable	Unit	Pacific NW	State		
			ID	OR	WA
CROP-LEVEL VARIABLES (means only), cont'd:					
Mean Water Applied[c]					
Alfalfa	acre-feet/farm	680	727	768	515
Barley	acre-feet/farm	447	551	336	242
Corn	acre-feet/farm	936	259	1,625	1,206
Dry Beans	acre-feet/farm	415	533	307	221
Wheat	acre-feet/farm	664	688	357	818
Base $P_c = CMCA$[c]					
Alfalfa	$/ton/NP	36.98	43.39	38.28	25.11
Barley	$/bushel/NP	1.65	1.74	1.47	1.61
Corn	$/bushel/NP	1.95	2.01	2.02	1.88
Dry Beans	$/cwt/NP	11.03	10.43	11.29	12.02
Wheat	$/bushel/NP	1.78	2.10	1.61	1.44

Note: Statistics are for farms growing at least two of five field crops with no specialty crop acreage. Descriptive statistics for farm-level soil variables and crop-level weather variables are not reported due to space constraints (but are available from the authors on request).

[a] NP represents the input price used as the numeraire price, bulk gasoline.

[b] Bulk gasoline is used as the numeraire price.

[c] Crop-level means apply only to the farms growing that particular crop. Farms not growing the crop are excluded from these calculations.

and Smathers; Boswell et al.; Hinman et al.).[10] Variable costs for each crop are computed using preplant, planting, growing, and harvesting costs. These variable costs enter directly as crop supply choke prices in the regime $P_c = CMCA$. An underlying assumption is that, for a given crop, its average variable cost equals marginal cost in the horizontal segment of the marginal cost function; thus, average cost can be used to represent $P_c = CMCA$. The final data on average variable cost reflect differences in irrigation application technology, in addition to any geographic distinctions contained in the Cooperative Extension Service budgets.

Estimates of Expected Producer's Surplus

Output supply functions for alfalfa, barley, corn, dry beans, and wheat are estimated using the tobit regression model. The supply functions are not discussed extensively because of their similarity to results in the literature (Moore, Gollehon, and Carey). (Appendix table A2 reports the supply function estimates.) Instead, we only note the performance of two variables in each equation, own-crop price and water price. The own-crop price determines the slope of the supply functions, while the coefficient on water price determines whether the supply curve shifts in or out in response to the experiments conducted later with water price. Each estimated coefficient on own-crop price

[10] The three crop budgets referenced are representative of 26 crop budgets from which information was taken for this study. The large number of budgets was needed to reflect differences across crops and states. A citation list for the entire set of budgets is available upon request from the authors.

is positive; three of five are significant at the 0.10 level in a one-tailed test. The estimated coefficients on water price are negative with alfalfa and corn, indicating that producers substitute away from these crops in response to higher water prices. The estimated coefficients are positive with barley, dry beans, and wheat. The estimates are statistically significant at the 0.10 level for alfalfa, barley, and dry beans.[11]

Using equation (5), estimates of expected producer's surplus for each crop are calculated for the three choke-price regimes. In addition to obtaining point estimates from regression coefficients, statistical properties of the surplus measures are computed using the Krinsky-Robb (K-R) method (Krinsky and Robb). The K-R method involves taking random draws on the parameter estimates, conditioned by the estimated mean and covariance matrix of the parameter vector. In this application, expected producer's surplus is computed for each draw, thereby producing a confidence interval for the surplus measure when combined across draws. While the K-R method can generate a confidence interval, and thus a median, it should not be used to generate moments of the distribution (Shonkwiler and Maddala).

Developing a confidence interval for $E[PS]$ contributes to the analysis in two ways. First, it accurately depicts the framework as a stochastic process. That is, the central tendency may be the expected value of producer's surplus, yet the probabilistic dispersion of producer's surplus also conveys important information. For example, the variability of $E[PS]$ could be incorporated into a benefit-cost analysis under uncertainty (Adamowicz, Fletcher, and Graham-Tomasi). Second, it helps to evaluate the measure of surplus generated from the regression coefficients, which is the conventional measure. If this measure is similar to the K-R median $E[PS]$, then the conventional measure can be used with more confidence.

For the sample of multicrop producers, summing across crops provides an estimate of expected producer's surplus from multicrop production. This is the farm-level, as opposed to a crop-specific, perspective. The choke-price regime $P_c = 0$ yields the highest estimate, \$72.87 million, for an average of \$123 per acre (table 2).[12] The other two regimes are closer in magnitude: the aggregate estimate is \$49.58 million (\$84 per acre) for $P_c = RPA$, and \$43.02 million (\$73 per acre) for $P_c = CMCA$.[13] Similar disparities across choke-price regimes were found in the case of estimating expected consumer's surplus (Hellerstein, p. 88).

Several general patterns emerge from the set of crop-specific results. (Note that the initial three comments abstract from evidence on the statistical dispersion of $E[PS]$ generated by the K-R method.) First, the relative magnitude of expected producer's surplus is consistent across crops regardless of choke-price regime (figure 2). From largest to smallest, the ordering of wheat, alfalfa, corn, barley, and dry beans remains intact.[14]

[11] The estimated coefficient on water price is significant at the 0.20 level in the wheat supply equation.

[12] These numbers are estimates of $E[PS]$ calculated from the regression coefficients, not those calculated with the K-R method. The K-R median yields similar estimates when summed across crops. For the choke-price regime $P_c = 0$, for example, the multicrop sum equals \$70.83 million for the K-R median.

[13] For comparative purposes, average cash rents per acre for irrigated cropland in 1988 were: \$91.20 in Idaho, \$81.50 in Oregon, and \$89.70 in Washington (USDA/ERS). These figures are quite close to the estimates of $E[PS]$ per acre for two choke-price regimes ($P_c = CMCA$ and $P_c = RPA$), while $P_c = 0$ is notably higher at \$123 per acre. The higher figure is similar to cash rents in 1993, which were \$100.50 in Idaho, \$124.70 in Oregon, and \$124.20 in Washington (USDA/ERS).

[14] The difference in $E[PS]$ across crops raises the question: Why not produce more of the high-value crops? This apparent anomaly of different values for $E[PS]$ across crops can be explained as the difference between an average and a marginal. The measures of $E[PS]$ and $E[PS]$ per acre represent an average return, not a marginal return. Thus, marginal net benefits may well be set equal across crops even though $E[PS]$ and $E[PS]$ per acre vary markedly across crops.

Table 2. Expected Producer's Surplus for the Sample, by Choke-Price Regime

Description	CROP					Farm-Level Total
	Alfalfa	Barley	Corn	Dry Beans	Wheat	
AGGREGATE:	($ millions)					
Choke Price $P_c = 0$	25.25	4.90	9.94	0.91	31.87	72.87
Choke Price $P_c = CMCA$	14.45	3.79	4.03	0.83	19.91	43.02
Choke Price $P_c = RPA$	15.58	3.17	4.44	0.06	26.32	49.58
PER ACRE:	($ per acre)					
Choke Price $P_c = 0$	171	37	266	44	126	123
Choke Price $P_c = CMCA$	98	28	108	40	79	73
Choke Price $P_c = RPA$	105	24	119	3	104	84

Notes: This table uses estimates of expected producer's surplus that are calculated from the regression coefficients, not those calculated with the Krinsky-Robb method. Levels of acreage are from predicted, rather than actual, crop acreage to conform with the predictive basis on which producer's surplus is calculated.

This ordering follows land use to a degree; predicted baseline land use (in thousands of acres) for the sample is as follows: wheat = 253, alfalfa = 148, barley = 134, corn = 37, and dry beans = 21. Corn leapfrogs barley in the ordering of $E[PS]$ relative to the ordering of acreage. Corn generates the largest $E[PS]$ per acre, while barley's $E[PS]$ per acre is relatively small (table 2).

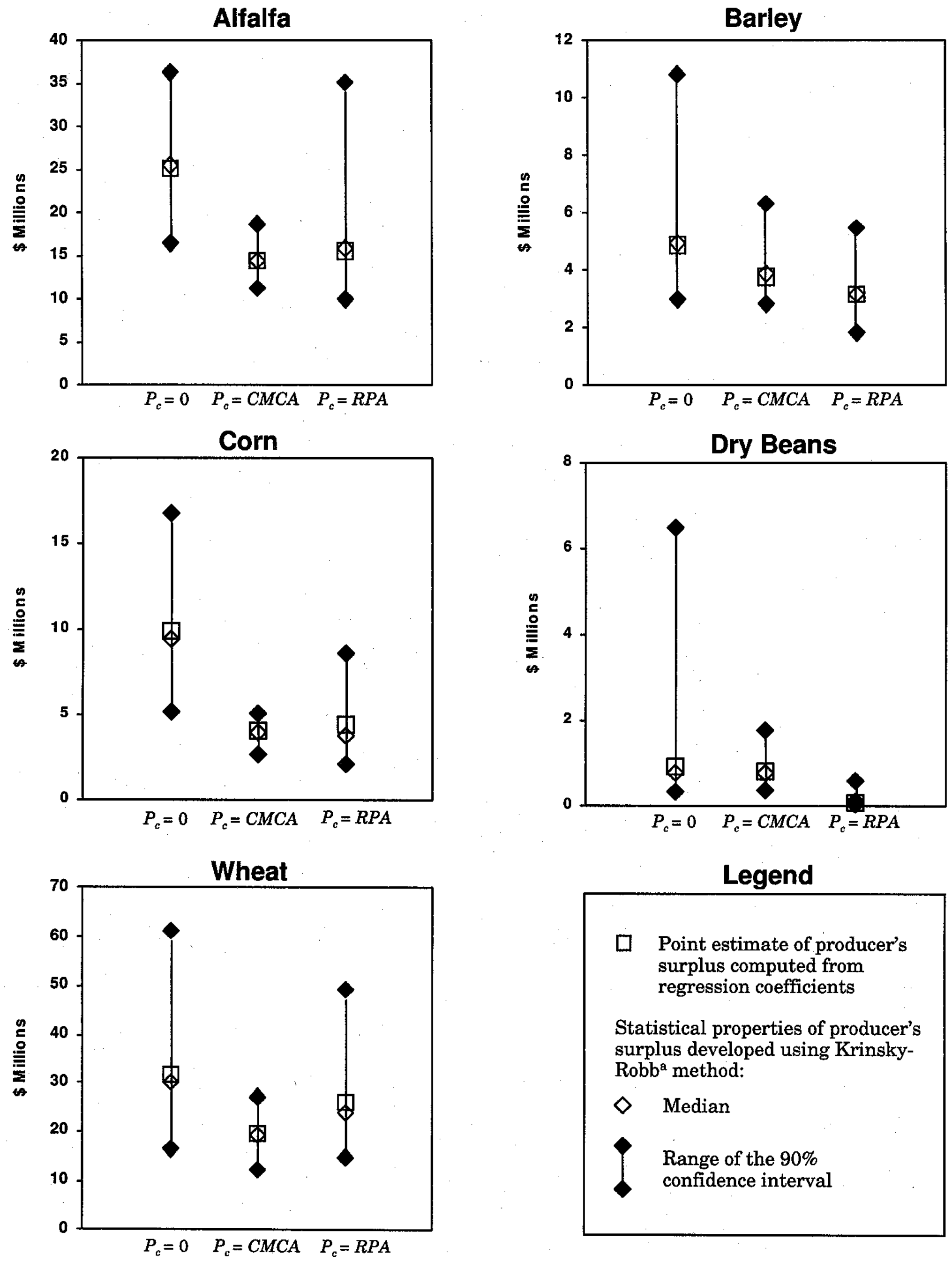
Second, comparison across choke-price regimes establishes the upper and lower bounds for estimates of $E[PS]$ by crop. The regime of $P_c = 0$ sets the upper bound, as described above. The regimes of $P_c = CMCA$ and $P_c = RPA$, whichever is lower for a given crop, provide a reasonable estimate of the lower bound. Relatively large absolute differences between lower and upper bounds occur with wheat, alfalfa, and corn. For the case of estimating $E[PS]$ from the regression coefficients (table 2), differences in bounds for these crops equal roughly \$12, \$11, and \$6 million, respectively.

Third, the regimes of $P_c = CMCA$ and $P_c = RPA$ generate comparable estimates for alfalfa, barley, and corn. This is a consequence of the particular data rather than reflective of an underlying relationship.

Fourth, estimates of $E[PS]$ derived from the regression coefficients are very similar to estimates of median $E[PS]$ derived using the K-R method (figure 2). Thus, estimates from the regression coefficients provide acceptable measures of the midpoint of the distribution.

Fifth, the dispersion of estimates of $E[PS]$, as generated by the K-R method, varies systematically by choke-price regime. For example, the range of the 90% confidence interval for $E[PS]$, by crop, generally falls in the descending order of $P_c = 0$, $P_c = RPA$, and $P_c = CMCA$ (figure 2). Moreover, most of the disparity across regimes occurs in the upper tails, not the lower tails, of the distributions. Two points explain this pattern. One, $P_c = CMCA$ generates the smallest surplus because it sets the choke price, instead of letting choke price vary with each random draw. This preempts large values of $E[PS]$. Two, for a given (hypothetical) draw, $P_c = RPA$ will generate a smaller estimate of $E[PS]$ than $P_c = 0$ whenever its choke price exceeds zero. Again, this tends to extend the upper tail of estimates for the regime $P_c = 0$.

An overriding conclusion from the exercise concerns the importance of choke price in estimating expected producer's surplus with a tobit regression model. As with expected



Note: Expected producer's surplus is calculated using equation (5) in the text, with three alternative regimes for setting the supply function's choke price (P_c).

[a] Statistical properties of aggregate expected producer's surplus were developed from 100 random draws on the tobit regression parameter estimates.

Figure 2. Aggregate expected producer's surplus for the sample, by choke-price regime

consumer's surplus, estimates of $E[PS]$ can vary significantly depending on choke price. The analysis produces three defensible estimates of the central tendency of producer's surplus, in addition to deriving a confidence interval for each estimate. This raises a question as to the proper course of action when developing an estimate of producer's surplus for a benefit-cost analysis. The question has a straightforward answer if one adopts the perspective that benefit-cost analysis is an exercise in collecting and organizing information and analysis (as opposed to producing a single number for a bottom-line benefit-cost ratio). From this perspective, the appropriate action would be to present the full set of results developed above.

Policy Experiment: The Columbia-Snake River Basin Salmon Recovery Program

Background

Salmon populations in the Columbia River Basin have declined severely as a result of river development and fish harvesting. Populations of salmon and steelhead have fallen to roughly 20% of their peak historic level of 10–16 million spawning adults per year; wild and naturally spawning salmon are at 2% of historic levels (Blumm and Simrin). Since 1991, three Snake River salmon stocks and four Columbia and Snake River steelhead populations have been listed as threatened or endangered under the federal Endangered Species Act (U.S. Department of Commerce 1995, 2000). Another 47 salmonid stocks may be at moderate to high risk of extinction in the Basin (Nehlsen, Williams, and Lichatowich).

Federal, state, and tribal governments are developing a multifaceted program to restore the Columbia River Basin salmon fishery (Columbia River SOR Interagency Team 1994a,b,c; Northwest Power Planning Council; U.S. Department of Commerce 1995, 2000).[15] A key component of the program involves improving conditions for in-river migration of salmon. One method of accomplishing this is to alter the timing and level of river flows through the lower Snake and lower Columbia Rivers. A range in the possible recovery measures needs to be assessed because decision makers have made only temporary decisions on river-flow management in the basin (Aillery et al. 1999; Blumm et al.).

Our analysis focuses on the effect of proposed river management alternatives on hydroelectricity prices. Bonneville Power Administration (BPA) supplies a large share of the Northwest's energy through its marketing of power from the region's federal hydroelectric facilities.[16] River management for salmon migration would decrease power

[15] The salmon recovery program is being developed under three related authorities. Under the Pacific Northwest Electric Power Planning and Conservation Act (1980), the Northwest Power Planning Council must design and implement a program that balances fish and wildlife with traditional uses of the Columbia River and related land resources. The Columbia River System Operation Review is considering river management options for the federal agencies with responsibility for managing the Columbia and lower Snake Rivers (Bonneville Power Administration, U.S. Army Corps of Engineers, and U.S. Bureau of Reclamation). And the National Marine Fisheries Service is responsible for leading the effort to recover the salmon runs listed under the Endangered Species Act.

[16] According to the *Columbia River System Operation Review Draft Environmental Impact Statement*: "The hydroelectric dams on the Columbia and Snake Rivers are the foundation of the Northwest's power supply.... Hydropower supplies approximately 74% of the generating capacity in the Pacific Northwest, and approximately 61% of the firm energy supply.... Today, BPA markets the power from 30 Federal dams and one nuclear plant in the Pacific Northwest and has built one of the largest and most reliable transmission systems in the United States.... The projects under review in this EIS account for over 95% of the Federal system's hydroelectric capability and 65% of the region's hydroelectric capability" (Columbia River SOR Interagency Team 1994b, p. 2-5).

generation at eight major federal facilities, causing increases in BPA wholesale power rates. We analyze three rate increases to reflect a range of possible increases in BPA wholesale rates: 3.2%, 11.6%, and 21.1%. These rate increases come directly from river management alternatives evaluated by the Columbia River SOR (1994b).[17]

For our purposes, the wholesale rates are converted to retail rates at a geographic level defined by sub-state agricultural production areas within the region. The conversion applies information on wholesale-retail conversion factors and the share of irrigation power use reliant on BPA power within the area, using procedures found in Aillery et al. (1996, appendix A). The geographic detail reflects the varied reliance by retail supply companies on BPA-provided power. For example, the three levels of BPA wholesale rate increases translate into retail irrigation rate increases in north-central Oregon of 1.8%, 6.6%, and 12%.[18] In southern Idaho, where BPA power provides a small share of retail supply, retail rates increase by much smaller amounts: 0.5%, 1.7%, and 3.1%. In general, farmers in Oregon would experience the largest retail rate increases, followed by Washington and then Idaho. A relevant aspect of the analysis, consequently, concerns quantifying the disparate impact on farmers across states.

Policy Experiment

The policy experiment involves evaluating the effect of water price increases on expected producer's surplus.[19] The three higher BPA power rates—after conversion to a set of retail price increases—feed directly into the formula for water pumping costs (contained in footnote 9). Every irrigator in the sample faces a higher water price (pumping cost) based on this adjustment. The average water prices (in $/acre-foot/numeraire price) for irrigators in the sample are as follows: baseline = 17.18, Experiment 1 = 17.32, Experiment 2 = 17.70, and Experiment 3 = 18.13.

To compute the change in expected producer's surplus, we apply the result that the effect of an input price change on producer's surplus can be evaluated with output supply functions (Just, Hueth, and Schmitz, p. 59). In this case, a water-price increase may either shift in or shift out a crop supply function, depending on whether the estimated coefficient on the water price variable is negative or positive in the function. Alfalfa and corn supply shift in, while barley, dry beans, and wheat supply shift out. Accordingly,

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[17] From its draft environmental impact statement, the Columbia River SOR Interagency Team (1994b) reports that a 3.2% increase corresponds to a scenario of "Current Operations," which "reflects operation of the Columbia River System with interim flow improvement measures in response to ESA listings of Snake River salmon" (p. 4-4). An 11.6% increase corresponds to a scenario of "Flow Augmentation," which "would provide more water to move fish down the river by setting flow targets for every month" (p. 4-4). In particular, the high spring and summer flows required under this scenario would decrease the generating efficiency of the hydropower system. The 21.1% increase corresponds to a scenario of "Natural River Operation," which "would draw down the four lower Snake River projects to near the original river elevation for 2 months" (p. 4-5). Power generation at these projects would be eliminated during the drawdown period. Notably, the power appendix for the final environmental impact statement, which was issued in November 1995, did not contain estimates of BPA wholesale rate increases.

[18] The study undertaken for the Columbia River System Operation Review also found sizable differences, in percentage terms, between wholesale and retail rates (Columbia River SOR Interagency Team 1994b, p. 4-63).

[19] Measurement of the change in producer's surplus may provide a reasonably accurate gauge of long-run producer welfare. The analysis holds constant only farm-level land and irrigation technology. To the extent that the water-price increases would primarily change cropping pattern, rather than total acres or technology, producer's surplus as measured here approaches long-run welfare. Empirical evidence indicates that irrigation technology adoption, at least, is quite insensitive to groundwater pumping cost (Negri and Brooks).

Table 3. Farm-Level Expected Producer's Surplus for the Sample: Krinsky-Robb Simulations and Water-Price Experiments

Description	Median	90% Confidence Interval Lower	90% Confidence Interval Upper
	($ thousands)		
Choke Price $P_c = 0$:			
Baseline	74,784	54,918	105,458
Deviations from Baseline			
▸ Experiment 1	-33	42	-110
▸ Experiment 2	-116	150	-392
▸ Experiment 3	-208	277	-706
Choke Price $P_c = CMCA$:			
Baseline	43,326	35,846	52,206
Deviations from Baseline			
▸ Experiment 1	-85	-46	-128
▸ Experiment 2	-304	-166	-460
▸ Experiment 3	-553	-301	-831
Choke Price $P_c = RPA$:			
Baseline	52,701	36,071	81,689
Deviations from Baseline			
▸ Experiment 1	-36	40	-125
▸ Experiment 2	-126	144	-441
▸ Experiment 3	-225	266	-795

Notes: Information on the median and 90% confidence interval is developed from 1,500 random draws on the parameter estimates from the tobit regressions that estimate crop supply functions. The three water-price experiments involve increases in wholesale power rates charged by Bonneville Power Administration of 3.2%, 11.6%, and 21.1%, respectively, by experiment. The wholesale rates are then converted to retail prices faced by producers for electricity used in water pumping, and are finally translated into higher water prices. The average normalized water prices (in $/acre-foot/numeraire price) for irrigators in the sample are: Baseline = 17.18, Experiment 1 = 17.32, Experiment 2 = 17.70, and Experiment 3 = 18.13.

following a water-price increase, crop-level $E[PS]$ decreases for alfalfa and corn and increases for barley, dry beans, and wheat.[20]

One distinctive element, relative to the standard analysis, arises with the choke-price regime of $P_c = CMCA$. Typically, a shift in (shift out) of a supply curve causes a decrease (increase) in expected surplus. In this regime, the assumption that the marginal cost function is constant over a range of production creates a second effect. An increase in water price shifts up the marginal cost function in its constant range, prior to where the upward-sloping supply function shifts. This causes a decrease in surplus *for a range of production* regardless of whether supply shifts in or out. In the case of the supply function shifting out, this influence can generate a net decrease in expected producer's surplus.

As in the baseline, the water-price experiments are evaluated using the K-R method (table 3). The water-price increases generate decreases in median farm-level (multicrop) aggregate expected producer's surplus ranging from $33,000 to $553,000 for the sample,

[20] A table of crop-level adjustments in $E[PS]$ in response to the water-price experiments is available from the authors. We focus on farm-level $E[PS]$ in the reported analysis.

depending on experiment and choke price. The summation across crops thus produces an anticipated result for the median values: while $E[PS]$ for some crops increases, the relationship of multicrop producer's surplus declining in water price describes the net effect at the farm level.

The water-price experiments can be summarized in general terms. (Note first that, because water pumping cost depends linearly on energy price, a percentage increase in energy price translates into an identical percentage increase in water pumping cost. Thus, percentage changes in retail energy prices and water prices can be used interchangeably.)

Experiment 1 involves retail price increases between 0.5% and 1.8%, depending on location in the Northwest; it produces decreases in median aggregate expected surplus equal to 0.04% ($P_c = 0$), 0.20% ($P_c = CMCA$), and 0.07% ($P_c = RPA$). Experiment 2 involves retail price increases between 1.7% and 6.6%, and produces decreases in median aggregate expected producer's surplus equal to 0.16% ($P_c = 0$), 0.70% ($P_c = CMCA$), and 0.24% ($P_c = RPA$). Experiment 3 involves retail price increases between 3.1% and 12%, and produces decreases in median aggregate expected producer's surplus equal to 0.28% ($P_c = 0$), 1.28% ($P_c = CMCA$), and 0.43% ($P_c = RPA$). One conclusion surfaces: at the median value, farm-level expected producer's surplus responds inelastically to water price.

Two points are relevant across choke-price regimes. First, the experiments generate quite similar results for $P_c = 0$ and $P_c = RPA$. These two regimes generated markedly different estimates of aggregate surplus, yet surprisingly similar estimates of the change in aggregate surplus for the median value and the 90% confidence interval. Second, the decline in surplus under $P_c = CMCA$ is much greater than in the other regimes. To a degree, this can be attributed to the effect (described above) of the shift up in constant marginal cost. Because of this effect, negative lower bounds of the 90% confidence interval occur with $P_c = CMCA$; with the other choke-price regimes, the lower bounds move into the positive range despite the water-price increase.

Output substitution plays an important role in mitigating the effect of the price increases. In response to higher water prices, irrigators produce lower quantities of crops with relatively high water requirements and higher quantities of crops with relatively low water requirements.[21] In the case with the largest effect ($P_c = CMCA$), the three water-price increases reduce median expected producer's surplus by $85,000, $304,000, and $553,000 (table 3).

Compare this to the naïve situation of no response, in which producers make no substitutions. This situation is assessed by computing water costs—that is, predicting water quantity on each farm in the sample, then multiplying by the farm-level water prices. Relative to the baseline, the three water-price increases result in incremental water costs of $174,000, $622,000, and $1,134,000. Substitutions thus reduce the effect of higher water prices by about 50% in the case of $P_c = CMCA$. The dampening effect of crop substitution is significantly greater in the other choke-price regimes.

Note also that these incremental water costs for the case of no substitutions exceed the upper bound of the 90% confidence interval in every choke-price regime (table 3).

[21] Land reallocation is the basis for the observed output substitution. Producers reallocate total cropland, with increases in barley, dry beans, and wheat acreage substituting for decreases in alfalfa and corn acreage (appendix table A1).

Table 4. Average Per Farm Decrease in Farm-Level Expected Producer's Surplus for the Sample, by State: Water-Price Experiments

Description	Idaho (252 farms)	Oregon (117 farms)	Washington (160 farms)
		($ per farm)	
Choke Price $P_c = 0$:			
▸ Experiment 1	24	188	88
▸ Experiment 2	75	667	319
▸ Experiment 3	131	1,197	569
Choke Price $P_c = CMCA$:			
▸ Experiment 1	87	256	206
▸ Experiment 2	298	940	762
▸ Experiment 3	544	1,701	1,388
Choke Price $P_c = RPA$:			
▸ Experiment 1	32	214	56
▸ Experiment 2	107	769	212
▸ Experiment 3	190	1,385	375

Notes: The three water-price experiments involve increases in wholesale power rates charged by Bonneville Power Administration of 3.2%, 11.6%, and 21.1%, respectively, by experiment. The wholesale rates are then converted to retail prices faced by producers for electricity used in water pumping, and are finally translated into higher water prices. The state average normalized water prices (in $/acre-foot/numeraire price) follow for the sample of irrigators within each state. For Experiment 1: Idaho = 18.91, Oregon = 14.22, and Washington = 17.11. For Experiment 2: Idaho = 19.13, Oregon = 14.68, and Washington = 17.65. For Experiment 3: Idaho = 19.40, Oregon = 15.20, and Washington = 18.26.

Consequently, the naïve case of no substitutions can be dismissed as empirically irrelevant.[22]

Little comparison can be made between this study and the analysis conducted under the Columbia River System Operation Review (Columbia River SOR Interagency Team 1994a,b,c) because the SOR study does not report sector-specific estimates of the effect of higher retail power rates on the agricultural sector. Procedurally, the application of microdata in our study is a relative strength. The SOR applies average elasticities for each sector in estimating surplus. Average elasticities can generate inaccuracies relative to observation-specific calculations.[23] At the same time, we develop estimates of aggregate producer's surplus only for the sample, while the SOR provides estimates for the entire Northwest region. This is a relative strength of the SOR analysis.

[22] This finding on the irrelevance of the naïve case of no substitutions has implications for the quality of one of the economic studies conducted under the Columbia River System Operation Review. Reservoir drawdown along the lower Snake River would increase pump lifts for irrigators pumping water directly from the reservoirs to irrigate alfalfa hay, apples, corn, potatoes, and wheat. In estimating the impact of increases in pump lifts, the federal agencies assumed that pumping-cost increases would not affect crop output or cropping pattern (Columbia River SOR Interagency Team 1994a, p. 3-4). The estimates reported there must be regarded as inaccurately high in light of our empirical results.

[23] Another study of irrigated agriculture (Connor, Glyer, and Adams) reinforces this idea in two empirical results: (*a*) differences in groundwater pumping depths translate into differences in irrigation electricity demand and price elasticities, and (*b*) elasticities computed at the mean do not equal more disaggregate elasticities.

One revealing perspective comes from computation of average expected producer's surplus per farm, by state (table 4).[24] Irrigators' heavy reliance on BPA power in Oregon and (to a lesser extent) Washington translates into much greater per farm impacts. For the choke-price regime of $P_c = 0$, for example, decreases in per farm producer's surplus across experiments are roughly eight times greater in Oregon and four times greater in Washington than in Idaho.

This comparison explains part of the economics underlying Idaho's political strategy for salmon recovery. In the early 1990s, the state of Idaho—especially in the form of then-Governor Cecil Andrus—strongly advocated a single salmon recovery measure, drawdown of the four reservoirs along the lower Snake River in southeastern Washington (Burtraw and Frederick; Stuebner). Reservoir drawdown would reduce mortality rates of juvenile salmon in migration to the Pacific Ocean. Experiment 3 of the water-price experiments represents the effect of a two-month drawdown of the four lower Snake reservoirs to natural river conditions. Recall that BPA retail power rates are predicted to increase 21.1% under this scenario. Expected producer's surplus of Oregon irrigators in the sample would decrease by roughly \$1,200 to \$1,700 per farm, depending on choke-price regime. Idaho irrigators, in contrast, would absorb losses ranging from about \$130 to \$550 per farm (table 4).[25]

Summary

This study transfers an empirical technique for estimating economic welfare from the consumer side to the producer side of the market. The common circumstance of a behavioral decision—namely, that both a consumer and producer may either choose a positive quantity, or be at a threshold of zero, in their respective markets—establishes an essential similarity in behavior. Using this similarity, we develop empirical procedures for estimating expected producer's surplus from output supply functions estimated with the tobit regression model.

The empirical application involved estimation of expected producer's surplus for multioutput producers of irrigated crops in the Pacific Northwest. The sample of producers in this region grow at least two of five field crops (alfalfa hay, barley, corn, dry beans, and wheat). Expected surplus is estimated for each crop, then summed across crops to obtain farm-level, or multicrop, producer's surplus. Wheat and alfalfa generate a large share of multicrop producer's surplus when aggregated for the sample.

As in the case of expected consumer's surplus, the choke-price regime applied in the computation significantly affects estimates of expected producer's surplus. Three distinct choke-price regimes are applied, with the resulting estimates providing an upper and lower bound to expected producer's surplus. Moreover, the statistical properties of each estimate of producer's surplus are developed using the Krinsky-Robb (K-R) method for deriving confidence intervals of nonlinear functions of parameter estimates. For a given

[24] Per farm estimates of farm-level expected producer's surplus, by state, are derived by disaggregating the aggregate estimates into state-specific estimates, then dividing by the number of observations in the sample for the state.

[25] A final comparison can be made to the effect of BPA wholesale rate increases on the residential sector. A 9% increase in BPA rates would increase the average residential electricity bill by \$36 per year (Kenworthy). This is comparable to Experiment 2, in which BPA wholesale rates increase by 11.6% (table 4). Not surprisingly, the average irrigated farm would experience a much greater absolute loss than the average household.

choke-price regime, expected producer's surplus computed from the coefficient estimates is similar in magnitude to the median expected producer's surplus computed using the K-R method. The dispersion of estimates generated by this method varies systematically by choke-price regime.

A policy experiment investigated the effect of higher pumping costs for water on crop-level and farm-level producer's surplus. Proposed measures to improve in-river salmon migration in the Snake and Columbia Rivers would increase hydroelectric prices—and thus pumping costs—in the Pacific Northwest. Three increases in wholesale power rates charged by the Bonneville Power Administration (BPA) are analyzed: 3.2%, 11.6%, and 21.1%. In every choke-price regime and price scenario, the median value of aggregate expected producer's surplus responded inelastically to the higher water prices.

The role of substitution opportunities provides an important connection between this study and the recreational demand literature. In this study, output substitution—expanding production of crops with relatively low water requirements and contracting production of crops with relatively high water requirements—explains the producers' ability to mitigate the effect of the price increases on producer's surplus. In particular, increases in water cost from the hypothetical case of not responding to the water-price increases fall outside the 90% confidence interval of producer's surplus adjustments. In effect, not responding is an empirically irrelevant case. This parallels the general finding in the recreation literature that estimates of consumer's surplus are significantly inflated when the analysis does not consider observed substitutes (e.g., Bockstael; Morey, Rowe, and Watson). Random utility models that explain the choice among recreation sites have been developed to capture these substitution possibilities. On the producer side, the multioutput production model offers a ready-made framework to account for the substitution opportunities faced by the producer.

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Appendix

Table A1. Predicted Output and Resource Use for the Sample: Water-Price Experiments

	CROP				
Description	Alfalfa	Barley	Corn	Dry Beans	Wheat
OUTPUT:	(000 tons)	(000 bu.)	(000 bu.)	(000 cwt)	(000 bu.)
Baseline	713.9	11,859	6,211	438.3	22,653
Experiment 1	712.3	11,886	6,199	439.8	22,673
Experiment 2	708.2	11,955	6,165	443.6	22,724
Experiment 3	703.5	12,036	6,127	448.0	22,783
LAND:			(000 acres)		
Baseline	147.9	133.8	37.4	20.7	252.7
Experiment 1	147.5	134.1	37.3	20.8	252.8
Experiment 2	146.6	134.8	37.1	21.0	253.1
Experiment 3	145.5	135.6	36.9	21.2	253.3
IRRIGATION WATER:			(000 acre-feet)		
Baseline	271.9	160.8	77.7	37.3	285.6
Experiment 1	271.6	160.9	77.8	37.3	285.9
Experiment 2	270.9	161.0	78.0	37.2	286.6
Experiment 3	270.0	161.2	78.2	37.0	287.4

Table A2. Definitions of Variables and Tobit Model Estimates of Crop Supply Functions

Independent Variable[a]	Definition	CROP: Alfalfa	Barley	Corn	Dry Beans	Wheat
OUTPUT AND INPUT PRICES:						
ALFPRC	Alfalfa hay price	41.14*	371.47	-4,587.06*	-566.16**	—
BARPRC	Barley price	5,046.71**	82,399.95*	-238,939.20	-16,594.78	—
CRNPRC	Grain corn price	-288.58	-16,643.43	39,000.52	—	-44,653.37*
DBNPRC	Dry beans price	—	—	—	2,244.47	-43,850.37*
WHTPRC	Wheat price	—	—	—	—	39,854.27
WTRPRC	Water price calculated as the farm-level energy for water pumping	-36.13**	656.41**	-1,103.33	120.56*	381.39
WAGE	Farm labor wage rate	874.21**	-7,848.38	-27,451.46	-6,442.91**	17,609.31**
FARM-LEVEL LAND CONSTRAINT:						
TOTACR	Total farm area in crop production	0.59**	11.54**	37.15**	1.23**	37.80**
OTHER EXOGENOUS VARIABLES:						
CLMCDD	Long-run base 55 cooling degree-days	0.18	-13.80**	265.21**	8.03**	12.94**
CLMPCP	Long-run precipitation	70.76	-1,467.22	3,584.64	536.00	-2,857.30*
DMSRWT	Surface water used on the farm (binary variable)	213.51	-9,497.31	-19,744.93	2,290.87	-8,220.13
SWBOTH	Both surface and ground water availability (binary variable)	38.68	-978.40	24,810.71	30.34	-9,347.77*
DMPRES	Pressurized irrigation technology on farm (binary variable)	565.26	4,409.55	-76,256.81*	-5,518.88*	10,914.27
ITBOTH	Both gravity and pressurized irrigation technology on farm (binary variable)	413.15	-1,126.81	58,903.32*	1,743.58	-21,767.85**
SAND	Relatively sandy soil (binary variable)	424.71	23,129.05*	-6,955.57	1,970.52	643.48
GOODSL	Soil w/relatively few use restrictions (binary variable)	-737.25**	-2,668.77	-26,461.04	461.91	24,589.31**
BADSL	Soil w/relatively many use restrictions (binary variable)	-35.65	-15,773.42*	-4,433.26	-1,964.04	-11,704.96
INTERCEPT		-17,365.20	-89,279.33	-458,785.20	18,052.67	547,545.50
SEE[b]	Standard error of the estimate	2,112.86	36,015.47	104,307.33	7,696.10	47,276.08
LLF	Log likelihood function value	-695.65	-617.59	-249.06	-313.71	-509.87

Notes: Dependent variable is *CROP OUTPUT*. Single and double asterisks (*) denote significance at the 0.10 and 0.01 levels, respectively.

[a] All prices for variables are normalized by the price of bulk gasoline. Refer to text table 1 for units.

[b] Dividing the estimated regression coefficients by the SEE produces normalized coefficients for the latent dependent variable model of the tobit.