Estimating accounting prices for common pool natural resources:A distance function approach

Phoebe Koundouri

Department of Economics, University of Reading, Reading, UK
Department of Economics and Centre for Social and Economic Research on the Global Environment, University College London, London, UK

Anastasios Xepapadeas

Department of Economics, University of Crete, Rethymno, Greece

[1] We extend existing methodology for estimating shadow prices for exhaustible natural resources to renewable resources with common pool characteristics, using groundwater in irrigated agriculture as an example. The resource's shadow price is defined in terms of a perfect foresight open loop Nash equilibrium. Furthermore, we introduce a new estimation approach and derive shadow groundwater scarcity rents by estimating a stochastic restricted distance function using duality results between distance and cost functions. This approach is appropriate when price information is not available or when cost, profit, or revenue functions representations are precluded because of violations of the required behavior assumptions. We use our results to study policy implications for groundwater management.

1. Introduction

[2] The accounting or shadow price (other terms used are in situ price or scarcity rent) of the stock of a natural resource reflects changes in the discounted value of the future flows in welfare associated with the use of the natural resource, resulting from changes in the resource's stock. As such these accounting prices convey information which is of great importance in a number of areas. In resource management this accounting price, along with the extraction costs, determines the resource's full cost. In the process of estimating the inclusive or total wealth of a nation, accounting prices are used for the valuation of the stock of natural capital [e.g., *Dasgupta and Mäler*, 2000]. In resource regulation shadow prices are used as a basis for designing taxes on a harvested or extracted resource to prevent overexploitation of a common pool resource and direct the system toward a socially optimal path [e.g., *Brock and Xepapadeas*, 2004].

[3] In a dynamic optimization framework, the resource's accounting price is determined by the derivative of the value function of the problem with respect to the resources stock, (this interpretation also holds in nonoptimizing frameworks [*Arrow et al.*, 2003]) or equivalently, in the Hamiltonian formulation of the problem, by the costate variable associated with the transition equation describing the evolution of the resource's stock. Despite however the profound importance of these prices and the ability to define them formally in terms of economic models, their estimation by using ''market observables'' faces severe difficulties, because in cases such as stocks of common pool resources, or stocks in vertically integrated resource industries, the corresponding markets for in situ stocks are missing.

[4] The purpose of this paper is to develop a methodological approach leading to the estimation of the accounting price of groundwater with common pool characteristics. We consider the very often encountered situation in irrigated agriculture where groundwater is used by farmers located above the aquifer. In such a case an estimate of groundwater's shadow price can be used to value the stock of water in green accounting calculations, to help design pumping taxes in order to mitigate externalities associated with groundwater use [*Howe*, 2002], or to test the empirical implications of Hotelling's principle. See *Berck* [1995] and *Koundouri* [2003] for a survey of the relevant literature.

[5] Shadow prices for the in situ stock of exhaustible natural resources have been estimated by *Halvorsen and Smith* (HS) [1984, 1991], for exhaustible natural resources without common pool characteristics, using a restricted cost function approach resulting from an optimization model associated with the firm's wealth maximization problem. Our paper extends the HS methodology in two ways. First we generalize the methodology, using the groundwater in irrigated agriculture as an example, to renewable resources with common pool characteristics. In doing so the resource's shadow price is defined in terms of a perfect foresight open loop Nash equilibrium. Second we introduce a new estimation approach and derive shadow groundwater scarcity rents and stock effects on groundwater extraction costs, by estimating a stochastic restricted distance function using

duality results between distance and cost functions. We chose this approach because when price information is not available, or alternatively when price information is available but cost, profit or revenue function representations are precluded because of violations of the required behavior assumptions, distance functions provide an excellent analytical tool for deriving efficient input shadow prices. Violations of conventional behavior assumptions are the norm rather than the exception in inefficiently managed and regulated industries like agriculture. The estimated technical firm-specific inefficiencies present in production technologies of agricultural firms in the sample under consideration, suggest that cost minimization is not the relevant behavior objective in the industry under investigation. This empirical result therefore provides support for the use of the distance function approach to deriving in situ resource shadow prices and stock effects on extraction costs.

[6] On the policy level we focus on the use of the estimated groundwater shadow price for regulating resource extraction under the assumption that farmers behave in a noncooperative way. Comparing this price with the optimal shadow price of groundwater (after internalization of all relevant externalities) allows the policy maker to identify the optimal tax to be imposed on extracting agents, as well as the welfare benefits that can be achieved via regulation. Finally, the proposed methodology allows estimation of farm-specific technical inefficiency measures that can be used by the regulator for competitive benchmarking (''yardstick competition'') in which taxes or subsidies granted to each farm are based on the costs of a similar (in terms of input mix) but more efficient firm.

[7] In section 2 we describe the relevant behavior model in the context of common pool groundwater extraction for irrigated agriculture. In section 3 we use the HS approach to derive the shadow price of a renewable common pool resource. In section 4, we build on HS and develop an information richer and potentially more efficient approach to estimating shadow prices. In general, our approach is relevant when cost, profit or revenue function representations are precluded due to existence of allocative inefficiency, or when the regulator uses firm-specific efficiency measures for competitive benchmarking. In section 5, we summarize our main findings and discuss the policy implications of the proposed methodology.

2. Behavioral Model

[8] We consider $i = 1, \ldots, N$ agricultural firms (or farms) located above an aquifer, which are vertically integrated in that they engage both in the extraction (production) and use of common access groundwater as an input in their agricultural production. Let $W_i(t)$ denote the quantity of water extracted (pumped) by firm i at time t. The transition equation describing the evolution of the groundwater stock in the aquifer is given by:

$$\dot{H}(t) = \frac{1}{AS}\left[F(H) - (1-f)\cdot\sum_{i=1}^{N} W_i(t)\right];\; F(H) = R - bH \quad (1)$$

Transition equation (1) represents a renewable resource model, where H is aquifer head (m) representing yearly effects of cumulative groundwater extraction on total resource stock. R and f are constant aquifer-specific hydrological parameters representing deterministic groundwater recharge (m^3/year) and the return flow of percolation back to the aquifer (pure number), respectively, while b reflects the natural rate of water losses. The aquifer's area (m^2) and water storage capacity as a function of its pore space volume (pure number) are represented by A and S, respectively. Without loss of generality we normalize $AS = 1$.

[9] Assuming separability between quantities of inputs used in groundwater extraction and agricultural production, agricultural output is produced according to:

$$Y_i = Y_i\left(X_i^p; T; W_i\left(X_i^w; H; T\right)\right) \quad (2)$$

where Y_i is firm-specific quantity of final output, X_i^p is a vector of firm-specific agricultural inputs other than groundwater, T is time, indexing technological change effects, and $W_i()$ is firm-specific output from the extraction subproduction function, that is, the firm-specific quantity of groundwater extracted. For notational simplicity, time (t) is suppressed hereafter. The extraction subproduction depends on inputs used in the extraction process X_i^w, H and T. The inclusion of aquifer H in the water extraction function reflects groundwater stock effect on water pumping. We assume that each farmer is sufficiently small, forms expectations about the time paths of the decision variables of the rest of the farmers and optimizes against them. The problem is an open loop dynamic game and its solution corresponds to a perfect foresight intertemporal Nash equilibrium. We doubt that the use of an alternative equilibrium concept such as the closed loop (feedback-subgame perfect) changes the substantive conclusions or the methodological advances that we are developing in this paper. With a positive market rate of interest r, the wealth maximization problem of the vertically integrated agricultural firm is

$$\max_{X_i^p; W_i} \int_0^{\infty} e^{-rt}\left[P_Y Y_i - P_p X_i^p - C_i^w\left(W_i; P_w; H; T\right)\right] dt \quad (3)$$

subject to equations (1), (2) and $H(0) = H_o$, where P_Y is the price of output, P_p is the vector of agricultural input prices, P_w is the vector of groundwater extraction input prices, and C_i^w is the minimal total cost function dual to the groundwater extraction subproduction function given by

$$C_i^w\left(W_i; P_w; H; T\right) = \min_{X^w}\left\{P_w X_i^w : W_i \geq W_i\left(X_i^w; H; T\right)\right\} \quad (4)$$

[10] The current value Hamiltonian for farm i is defined as:

$$\mathcal{H}^i = P_Y Y_i - P_p X_i^p - C^w\left(W_i; P_w; H; T\right) + \mu^i\left[R - (1-f)\left(W_i + \sum_{l \neq i}^{N} W_l\right) - bH\right]$$

Assuming symmetry the optimality conditions characterizing the perfect foresight open loop Nash equilibrium are:

$$P_Y \frac{\partial Y}{\partial X_j^P} = P_{pj}$$

for the jth input

$$P_Y \frac{\partial Y}{\partial W} - \frac{\partial C^w}{\partial W} = \mu$$

$$\dot{\mu} - r\mu = \frac{\partial C^w}{\partial H}$$

along with equation (1) and the transversality condition at infinity. From the optimality conditions the costate variable μ is the groundwater shadow price emerging from farmers' noncooperative behavior with respect to water pumping, while $\frac{\partial C^w}{\partial H}$ reflects stock effects on the water extraction function.

[11] If we consider the social welfare maximization problem, then a planner maximizes net surplus from irrigated agriculture, or

$$\max_{X^p;W} \int_0^\infty e^{-rt} \left[\int_0^Y p(u)du - P_p X_i^p - C^w(W_i; P_w; H; T) \right] dt$$

where $p(u)$ is the demand function for the agricultural product, subject to equation (1). The costate variable, say λ, associated with equation (1), reflects the accounting price of the resource along the socially optimal path, and the difference $\lambda - \mu$ can be used, as shown in the concluding section, to design regulatory schemes. It can be shown that under appropriate assumptions $\lambda > \mu$ at a steady state equilibrium, which is a result of common pool externalities.

3. Restricted Cost Function Approach

[12] If a competitive market existed for groundwater, its market price in each t would observable. Because groundwater is owned in common, no market arises and this price becomes unobservable. To derive this price, HS use duality theory and derive the relationship between gross and final (refined) resource indirect cost function (empirical application of HS was for unextracted ore used by the Canadian metal mining industry). Duality theory suggests that the maximization problem (3) corresponds to the following unrestricted cost minimization problem

$$\min_{X^p;X^w} P_p X^p + P_w X^w + \mu[W(X^w; H; T)] \quad s.t.: Y(X^p; W; T) \geq Y \qquad (5)$$

where μ is the costate variable in the Hamiltonian of problem (3), which is the in situ shadow price (scarcity rent) of groundwater. The solution of equation (5) requires information on μ which cannot be obtained from market data. The problem has been addressed by HS by considering the auxiliary problem of minimizing the total cost of all inputs used in the production process (excluding groundwater) in each t, given H, Y, W in each t. In this restricted auxiliary problem, Y^* and W^* are the solutions to the firm's wealth-maximizing problem

$$\min_{X^p;X^w} P_p X^p + P_w X^w$$
$$\text{subject to } Y(X^P; W; T) \geq Y^* \quad \text{and} \quad W(X^w; H; T) \geq W^* \qquad (6)$$

[13] Each individual firm will not explicitly solve equation (6). Instead it will solve simultaneously for the wealth-maximizing quantities of output and rate of groundwater extraction, together with the quantities of agricultural inputs that minimize total costs. However, the optimal quantities of agricultural inputs given by the solution to equation (6) will be identical to the quantities implied by equation (3), the wealth maximization problem [see *Lau*, 1976]. The solution of equation (6) results in the restricted minimum cost function

$$C^R = C^R(Y; W; H; T; P_p; P_w)$$

Following HS in using the first-order conditions for equations (5) and (6) the envelope theorem to take the derivatives of equations (5) and (6), with respect to W and H, and then combining the results, the following proposition can be stated.

[14] Proposition 1 is as follows: The accounting price of the groundwater stock of a renewable common pool aquifer used for irrigated agriculture, corresponding to a symmetric perfect foresight open loop Nash equilibrium, is obtained as

$$\frac{\partial C^R}{\partial W} = -\mu \qquad (7)$$

The stock effects associated with changes in the groundwater head are obtained as

$$\frac{\partial C^R}{\partial H} = \dot{\mu} - r\mu$$

Thus the shadow price for groundwater can be derived by differentiating the estimated restricted cost function C^R with respect to gross production of groundwater, while stock effects are estimated by differentiating the same function with respect to the aquifer's head. Here, it is important to note that derivation of implicit shadow prices is possible for any values of μ and Y_i, not just those associated with wealth maximizing paths. That is, the restricted-cost function and Shephard's lemma are valid for any values of output (Y) and unpriced input (W), while the dynamic optimality conditions that must be imposed in order to obtain an equation for (μ) in the renewable resource context hold only at the optimum. Intuitively, although relation (7) is derived by assuming statically profit-maximizing agents, it holds for resource rents which are derived from both optimal and suboptimal dynamic resource management. For example, it holds where groundwater is suboptimally extracted over time, as is the case in general under common property.

4. Distance Function Approach

[15] The pioneering theoretical work on distance functions in production theory dates back to *Shephard* [1970], and recent extensions were made by *Färe et al.* [1994] and *Färe and Primont* [1995]. Empirical applications that compute shadow prices of either inputs or outputs in regulated industries are more recent and include, among others, *Grosskopf and Hayes* [1993] and *Färe et al.* [1993].

[16] In empirical applications, distance functions have a number of virtues: (1) they do not necessarily require price data to compute the relevant parameters, only quantity data is needed; (2) they do not impose any behavioral hypothesis (i.e., profit maximization or cost minimization); and (3) they

allow the derivation of firm-specific inefficiencies. In resource management problems these are considerable advantages, given (1) absence of reliable price data for natural resource inputs, (2) diversity of firms' objectives when they are heavily regulated, and (3) inefficiencies arising due to regulation or nonoptimal management of natural resource industries.

[17] By using Shephard's input distance function (an input orientation may be more appropriate in agriculture because the managers are likely to have more discretionary control over inputs rather than outputs) to characterize technology rather than a cost function, we can employ a dual Shephard's lemma to retrieve firm and input specific shadow prices [*Färe and Grosskopf*, 1990]. The restricted input distance function for the ith agricultural firm is defined as

$$D_i^R(Y_i; X_i^p; X_i^w; W_i; H; T) = \max\left\{\phi_i > 0 : \left(\frac{X_i}{\phi_i}\right) \in L(Y_i; W_i; H; T)\right\} \quad (8)$$

where X_i denotes firm-specific vector of m input quantities ($X_i = (X_i^p, X_i^w) \in R^m$), $L(Y_i, W_i, H, T) = \{X_i \in R_+^m : X_i$ can produce $Y_i \in R_+\}$ denotes the set of all input vectors which can produce the output vector ($Y \in R_+$); and ϕ_i measures the proportional (or radial) reduction in all ($X \in R_+^m$) that brings the ith firm to the frontier isoquant. The set $L(Y)$ satisfies (1) $0 \notin L(Y)$, $Y \geq 0$, $Y \neq 0$; (2) $X \geq Y\, L(Y) \Rightarrow X \in L(Y)$; (3) $L(Y)$ is convex; (4) $L(Y)$ is closed; (4) $L(\theta Y) \subseteq L(Y)$, $\theta \geq 1$. In equation (8) we assume existence of a maximum, i.e., $\phi = +\infty$ not possible. Given the restricted cost function in equation (9), *Shephard* [1970] showed that the restricted input distance function may also be obtained as a price minimal cost function as shown in equation (10).

Given the general axioms describing the production set, the restricted input distance function is (1) nondecreasing in ($X \in R_+$) and increasing in ($Y \in R_+$); (2) linearly homogeneous in ($X \in R_+$); (3) $D_i^R(\,) \geq 1$ if ($X \in R_+$) $\in L^R(\,)$; and (4) $D_i^R(\,) = 1$ if ($X \in R_+$) belongs to the frontier of the input set.

$$C_i^R(Y_i; P_p; P_w; W_i; H; T) = \min_{X_i^p; X_i^w}\left\{P_p X_i^p + P_w X_i^w : D_i^R(Y_i; X_i^p; X_i^w; W_i; H; T) \geq 1\right\} \quad (9)$$

$$D_i^R(Y_i; X_i^p; X_i^w; W_i; H; T) = \min_{P^p; P^w}\left\{P_p X_i^p + P_w X_i^w : C_i^R = C_i^R(Y_i; P_p; P_w; W_i; H; T)\right\} \quad (10)$$

The Lagrangian of the cost minimization problem postulated in equation 9) is

$$\Lambda_i = P_p X_i^p + P_w X_i^w + \phi_i\left[1 - D_i^R(Y_i; X_i^p; X_i^w; W_i; H; T)\right] \quad (11)$$

Applying the envelope theorem to equation (11) gives:

$$\frac{\partial C_i^R}{\partial W_i} = \frac{\partial \Lambda_i}{\partial W_i} = -\phi_i \frac{\partial D_i^R}{\partial W_i} \quad (12)$$

$$\frac{\partial C_i^R}{\partial H} = \frac{\partial \Lambda_i}{\partial H} = -\phi_i \frac{\partial D_i^R}{\partial H} \quad (13)$$

The first-order conditions with respect to input quantities is:

$$\frac{\partial C_i^R}{\partial X_i^p} = \frac{\partial \Lambda_i}{\partial X_i^p} = P_p - \phi_i \frac{\partial D_i^R}{\partial X_i^p} = 0 \quad (14)$$

$$\frac{\partial C_i^R}{\partial X_i^w} = \frac{\partial \Lambda_i}{\partial X_i^w} = P_w - \phi_i \frac{\partial D_i^R}{\partial X_i^w} = 0 \quad (15)$$

The first-order conditions with respect to input prices is

$$\frac{\partial C_i^R}{\partial P_p} = \frac{\partial \Lambda_i}{\partial P_p} = X_i^P \quad (16)$$

$$\frac{\partial C_i^R}{\partial P_w} = \frac{\partial \Lambda_i}{\partial P_w} = X_i^w \quad (17)$$

$$\frac{\partial C_i^R}{\partial \phi_i} = 1 - D_i^R(\cdot) = 0 \quad (18)$$

Following *Shephard* [1970], $\phi = \Lambda = \hat{C}^R(\,)$ at the optimum, where $\hat{C}^R(\,)$ is the minimum restricted cost (Lemma: Let $v(p) = \max_x\{px: G(x) \leq 1\}$, $p, x \in R^m$, $G(mx) = mG(x)$ for every $x \in R^m$ and $m > 0$. Then $v(p) = \lambda(p)$ where $\lambda(p)$ is the optimal Lagrangian multiplier associated with $L(x, \lambda) = px + \lambda[1 - G(x)]$.) However, $\hat{C}^R(\,)$ depends on the shadow prices we seek. Therefore, in order to obtain $\hat{C}^R(\,)$ we adopt the assumption suggested by *Färe and Grosskopf* [1990, p. 125] that firms satisfy a balanced budget. Thus minimum restricted cost can be retrieved since costs must equal revenues and when the distance function (8) is known, we can estimate the derivatives of the restricted cost function from the restricted distance function using

$$-\frac{\partial D_i^R}{\partial W_i} \hat{C}_i^R = \frac{\partial C_i^R}{\partial W_i} \quad (19)$$

$$-\frac{\partial D_i^R}{\partial H} \hat{C}_i^R = \frac{\partial C_i^R}{\partial H} \quad (20)$$

Going back to proposition 1 and using equations (19) and (20), proposition 2 can be stated as follows: The accounting price of the groundwater stock of a renewable common pool aquifer used for irrigated agriculture, corresponding to a symmetric perfect foresight open loop Nash equilibrium, is equal to the absolute shadow price of the resource derived from the restricted input distance function that describes firm-specific technology, or

$$-\frac{\partial D_i^R}{\partial W_i} \hat{C}_i^R = \mu_i \quad (21)$$

In the same context the stock effects associated with changes in the groundwater head are obtained as

$$-\frac{\partial D_i^R}{\partial H} \hat{C}_i^R = \dot{\mu}_i - r\mu_i = \frac{\partial C_i^R}{\partial H} \quad (22)$$

5. Econometric Specification, Empirical Estimation, and Results

[18] The assumption that $L_i(\,)$ is a closed convex set, implies that the two approaches (8) and (10) yield the same

distance function [*Shephard*, 1970]. It follows that $D_i^R(\,)$ can be calculated using the formulation in equation (8) which requires data on input and output quantities. We estimate equation (8) using a translog stochastic input distance function [*Aigner et al.*, 1977] for the case of K inputs and M outputs. To obtain the frontier surface (i.e., the transformation function) we set $D_i = 1$. Moreover we impose (1) the restrictions required for homogeneity of degree +1 in inputs, $\sum_{k=1}^{K} \beta_k = 1$; $\sum_{l=1}^{K} \beta_{kl} = 0$ for $k = 1, 2, \ldots, K$; and $\sum_{k=1}^{K} \delta_{km} = 0$ for $m = 1, 2, \ldots, M$; (2) the restrictions required for symmetry, $\alpha_{mn} = \alpha_{nm}$ for $m, n = 1, 2, \ldots, M$ and $\beta_{kl} = \beta_{lk}$ for $k, l = 1, 2, \ldots, K$; and (3) the condition required for separability between inputs and outputs, $\delta_{km} = 0$ for $k = 1, 2, \ldots, K$ and $m = 1, 2, \ldots, M$.

$$\ln(D_i/x_{Ki}) = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mi} \ln y_{ni} + \sum_{k=1}^{K-1} \beta_k \ln x^*_{ki} + \frac{1}{2}\sum_{k=1}^{K-1}\sum_{l=1}^{K-1} \beta_{kl} \ln x^*_{ki} \ln x^*_{li} + \sum_{k=1}^{K-1}\sum_{m=1}^{M} \delta_{km} \ln x^*_{ki} \ln y_{mi}$$
$$i = 1, 2, \ldots, N \quad \text{and} \quad x^*_k = x_k/x_K \qquad (23)$$

where i denotes the ith firm in the sample. (Note homogeneity implies $D(y, \omega x) = \omega D(y, x)$ for any $\omega > 0$; we arbitrarily choose one of the inputs and set $\omega = 1/x_K$. Hence $D(y, x/x_K) = D(y, x)/x_K$.) The frontier function has an error term with two components. The first component is a symmetric error term (V_i) that accounts for noise, which is assumed identically and independently distributed with zero mean and constant variance [$iid \sim N(0, \sigma_V^2)$]. The second component is an asymmetric error term (U_i) that accounts for technical inefficiency, which is assumed to follow an *iid* distribution truncated at zero ($N(\mu, \sigma_U^2)$). The two components of the error term, V_i and U_i, are independent. Predictions for $D_i = \exp(U_i)$ are obtained using the conditional expectation $D_i = E[\exp(U_i)|W_i]$, where $W_i = V_i - U_i$. Changing notation ln (D_i) to U_i, equation (23) becomes

$$-\ln(x_{Ki}) = TL\left(y_i, \frac{x_i}{x_{Ki}}; \alpha, \beta\right) + V_i - U_i \qquad i = 1, 2, \ldots, N \qquad (24)$$

[19] Data sources and variables' definitions are provided in Appendix A. Equation (24) is estimated by maximum likelihood. Results are presented in Table 1. Estimated parameters have the anticipated signs (positive for inputs and negative for outputs). Gross products and squared coefficients are not reported because they were excluded from the empirical model after a preliminary estimation which indicated that their estimated effects were not significantly different from zero. Hence the stochastic distance function estimated in this paper has a restricted translog form in which all second-order parameters associated with inputs are set to zero. This formulation imposes separability between inputs and outputs. The coefficient of v is not significantly different from zero, suggesting support for the half-normal distribution for inefficiency effects. The calculated one-sided likelihood ratio (LR) test strongly suggests rejection of the null hypothesis of no technical inefficiency effects in the truncated-normal model. If the null hypothesis is true, then the generalized LR statistic is asymptotically distributed as a mixture of chi-square distributions. The critical value for this mixed chi-square distribution is 5.138 for a 5% level of significance (taken from Table 1 of *Kodde and Palm* [1986]). Moreover, a zero value for γ ($\gamma = \sigma_U^2/(\sigma_U^2 + \sigma_V^2)$) indicates that the deviations from the frontier are entirely due to noise, while a value of one indicates that all deviations are due to technical inefficiency. It should be stressed, however, that γ is not equal to the ratio of the variance of the technical inefficiency effects to the total residual variance. This is because the variance of U_i is equal to $[(\pi - 2)/\pi]\sigma^2$, not σ^2. Both hypotheses, $\gamma = 0$ and $\gamma = 1$, are rejected at the 95% level of significance, supporting the existence of technical inefficiency and the choice of a stochastic model, respectively.

Table 1. Estimated Parameters for the Input Distance Function[a]

Variable	Parameter	ML Estimates	T Ratios[b]
Constant	α_0	−0.48	0.60
Output	α_1	−0.30	5.68
Nonirrigated land	β_1	0.28	9.44
Labor	β_2	0.19	4.02
Costs	β_3	0.04	0.81
Water extraction	β_4	0.09	4.15
Head	β_5	0.02	1.98
Irrigated land	by homogeneity	0.38	
Irrigated land	log (likelihood)	378.14	
Irrigated Land	LR test	226.71	−1.37
Irrigated land	$\gamma = \sigma_U^2/(\sigma_U^2 + \sigma_V^2)$	0.88	1.36
Irrigated land	η	1.40	2.02

[a]The dependent variable is irrigated land. Number of cross sections is 76; number of time periods is 3.

[b]Hypothesis tests are carried out at 95% confidence level.

[20] Moreover, given the availability of panel data we are able to test for time-varying technical efficiencies. Following *Battese and Coelli* [1992], technical inefficiency effects in our model are assumed to be defined by:

$$U_{it} = (U_i \exp(-\eta(t - T))) \qquad (25)$$

where U_is are assumed to be *iid* as the generalized truncated-normal random variable defined above, and η is a parameter to be estimated. If the hypothesis that $\eta = 0$ is accepted, then we can conclude that firm-specific inefficiencies are time invariant. In the specification of equation (24), if the ith firm is observed in the last period of the panel T, then $U_{iT} = U_i$, because the exponential function $\exp(-\eta(t - T))$ has a value of one when $t = T$. Thus the random variable, U_i, can be considered as the technical inefficiency effect for the ith firm in the last period of the panel. For earlier periods in the panel, the technical efficiency effects are the product of the technical inefficiency effect for the ith firm in the last period of the panel and the value of the exponential function $\exp(-\eta(t - T))$, whose value depends on the parameter η, and the number of periods before the last period of the panel, $-(t - T) = T - t$. If the parameter η is positive, then $-\eta(t - T) = \eta(T - t)$ is nonnegative and so $\exp(-\eta(t - T))$ is no smaller than one, which implies that $U_{it} \geq U_i$. The calculated t-statistic for η reported in Table 1 indicates that the estimated coefficient for η is significantly different

Table 2. Predicted Technical Efficiency Estimates[a]

Year 1991			Year 1997			Year 1999		
Firm 1–26	Firm 27–52	Firm 53–76	Firm 1–26	Firm 27–52	Firm 53–76	Firm 1–26	Firm 27–52	Firm 53–76
0.58	0.56	0.10	0.86	0.85	0.52	0.96	0.96	0.85
0.54	0.61	0.35	0.84	0.87	0.74	0.96	0.97	0.92
0.54	0.29	0.20	0.84	0.70	0.62	0.96	0.91	0.89
0.53	0.29	0.10	0.83	0.69	0.53	0.95	0.91	0.85
0.60	0.60	0.43	0.88	0.86	0.78	0.96	0.96	0.94
0.54	0.68	0.17	0.84	0.90	0.60	0.96	0.97	0.87
0.53	0.55	0.08	0.83	0.84	0.49	0.95	0.96	0.84
0.54	0.61	0.17	0.84	0.87	0.60	0.96	0.97	0.88
0.53	0.64	0.70	0.84	0.88	0.91	0.96	0.97	0.98
0.66	0.27	0.66	0.89	0.68	0.89	0.97	0.91	0.97
0.62	0.07	0.69	0.87	0.49	0.90	0.97	0.83	0.97
0.30	0.20	0.73	0.70	0.62	0.92	0.91	0.88	0.98
0.45	0.61	0.05	0.79	0.87	0.42	0.94	0.97	0.81
0.43	0.13	0.08	0.78	0.55	0.49	0.94	0.86	0.84
0.42	0.18	0.68	0.78	0.61	0.90	0.94	0.88	0.97
0.44	0.66	0.71	0.79	0.90	0.91	0.94	0.97	0.98
0.47	0.62	0.69	0.80	0.87	0.90	0.94	0.97	0.97
0.63	0.30	0.61	0.88	0.70	0.87	0.97	0.91	0.97
0.43	0.52	0.61	0.78	0.83	0.87	0.94	0.95	0.97
0.39	0.53	0.60	0.76	0.83	0.87	0.93	0.95	0.96
0.47	0.51	0.70	0.80	0.82	0.90	0.95	0.95	0.97
0.36	0.58	0.67	0.74	0.86	0.90	0.93	0.96	0.97
0.58	0.33	0.66	0.86	0.72	0.89	0.96	0.92	0.97
0.52	0.64	0.72	0.83	0.88	0.91	0.95	0.97	0.98
0.48	0.55		0.81	0.84		0.95	0.96	
0.25	0.05		0.67	0.44		0.90	0.81	

[a]Mean efficiency in 1991 is 0.47. Mean efficiency in 1997 is 0.78. Mean efficiency in 1999 is 0.94.

from zero and positive. This result suggests that firm-specific technical efficiencies are increasing over time.

[21] Firm-specific technical efficiencies are reported in Table 2. Technical inefficiency implies use of an excessive amount of inputs to produce the fixed output levels and is clearly related to the lack of incentives faced by the operators of the firm. Allocative inefficiency implies use of an economically suboptimal input mix when market prices are considered and could be caused by exterior environmental constraints under which managers operate. The existence of technical inefficiency alone does not necessarily imply biased cost function estimates (other than some bias in the intercept parameter, which will not affect the shadow price estimates). Unfortunately, relevant price data was not available and the existence of allocative inefficiency could not be tested, but if it exists our estimates of scarcity rents are unbiased. Technical inefficiency measures, however, can be used by the regulator for competitive benchmarking (''yardstick competition'') in which taxes or subsidies granted to each farm are based on the costs of a similar (in terms of input mix) but more efficient firm. Such a regulatory framework can (1) increase the managers' of the farms incentives toward efficiency and (2) reduce the informational asymmetry between the managers of the farms (agent) and the regulators or consumers of agricultural products (the principal). A problem that needs to be addressed is the risk of collusion among firms in a dynamic game.

[22] In Table 3, mean per cubic meter shadow price estimates are calculated using Proposition 2. The mean annual per farm minimum restricted cost function $\hat{C}_i^R$ is approximated by the mean annual per farm revenue, which is measured in Cyprus pounds, 1999 constant prices. For the justification of this approximation, see *Halvorsen and Smith* [1984, 1991]. The change in the restricted distance function per unit change in groundwater extraction $\frac{\partial \ln D_i^R}{\partial \ln W_i}$, measured in pounds per cubic meter, is the estimated parameter of the quantity of groundwater extraction from the stochastic distance function estimation, the results of which are presented in Table 1. Moreover, D_i^R and W_i are respectively the mean annual estimated distance function and mean groundwater extraction per farm, measured in £/m^3 and m^3. The mean shadow value of the per cubic meter in situ groundwater calculated in Table 3 is slightly increasing over the years, but is very small. These values are calculated by taking into account that our empirical results give estimates of the derivatives of the natural logarithm of the input distance function, which equal

$$\frac{\partial \ln D}{\partial \ln W} = \frac{W}{D}\frac{\partial D}{\partial W}$$

where $D = E[\exp(U)|W]$. If a long enough time series of data were available, one could test the implications of the Hotelling principle by following exactly the same procedure that *Halvorsen and Smith* [1984, 1991] suggested.

[23] It is also interesting to note from Table 1 that the estimate of the coefficient for the head of the aquifer is significantly different from zero. This implies the existence of stocks effects which can be estimated using Proposition 2

Table 3. Mean Groundwater Scarcity Rents

Year	$\hat{C}_i^R$	$\frac{\partial \ln D_i^R}{\partial \ln W_i}$	D_i^R	W_i	μ_i
1999	£4312.33	£0.09/m^3	1.06 m^3/£	42567.34 m^3	£0.0097 m^3
1997	£5003.56	£0.09/m^3	1.22 m^3/£	62000.76 m^3	£0.0089 m^3
1991	£5687.39	£0.09/m^3	1.53 m^3/£	88978.90 m^3	£0.0088 m^3

Table 4. Mean Stock Effects on Groundwater Extraction Cost

Year	$\partial C_i^w/\partial H$, £/m^3/m of head
1999	0.00215
1997	0.00197
1991	0.00196

as $\frac{\partial C_i^w}{\partial H} = -\frac{\partial D_i^R}{\partial H}\hat{c}_i^R$. The results are shown in Table 4. Stock effects are increasing with scarcity, as expected, but they are relatively small, which is another indication supporting the argument of myopic behavior of the extracting agents.

6. Conclusions and Policy Implications

[24] In this paper we develop a new methodology for estimating the in situ shadow price of a renewable natural resource with common pool characteristics. Our starting point is the observation that the restricted cost function that has been used recently for this purpose might not be appropriate in cases where profit maximization or cost minimization does not prevail. To estimate the in situ shadow prices in a framework independent of cost minimization restrictions, we develop a methodology based on the input distance function, which does not impose any behavioral assumptions. The resulting evidence on failure of farmers to minimize costs, provides support for the use of the distance function and proves the potential for estimation inaccuracy should one wrongly choose to use the restricted distance function methodology. The proposed methodology can be used to estimate shadow prices for renewable resources such as groundwater, forest and fisheries.

[25] The distance function methodology for estimating scarcity rents has been applied to the irrigated agricultural sector of the Kiti region of Cyprus. The existence of inefficiencies revealed by the estimation of the distance function supports the idea that the distance function approach in estimating scarcity rents may be, in this case, more appropriate than the restricted cost function approach.

[26] It is also interesting to compare the derived partial equilibrium shadow price of in situ groundwater (which as already argued, is an estimate of the individual farmer's valuation of the marginal unit of groundwater in the aquifer) with the socially optimal shadow price of in situ groundwater derived for the Kiti aquifer in 1999 by *Koundouri and Christou* [2000]. In this paper an optimization model, which is simulated under conditions of optimal groundwater extraction, determines the in situ value of the resource to be £0.2017 per cubic meter of water. This is approximately 21 times larger than the corresponding value derived in this paper for year 1999. What could rationalize this divergence? This can be rationalized in the presence of noncooperative behavior and common pool externalities. Current users of the resource are willing to pay only the private cost (the private cost of resource extraction is the cost of pumping one cubic meter of water per meter of lift and equals £0.02) and not the full social cost of their resource extraction. As a result the resource's scarcity value goes unrecognized. This pattern of behavior is consistent with perfectly myopic (i.e., dynamically inefficient) resource extraction, which can be rationalized by the nonexistence of the appropriate institutional foundations that provide farmers with the incentive to pay today for conserving in situ groundwater for future extraction. Myopic behavior is also supported by the low estimated stock effects. Hence the need for optimal management of this aquifer emerges, so that current users of the resource pay the social cost of their groundwater extraction and not just its private component.

[27] Given an estimate of the optimal (unit) resource rents and the distance function measure, the optimal pricing policy is the difference between the two. Moreover the significant improvement in welfare realized by simulating optimal extraction from the Kiti aquifer compared to the common property extraction [*Koundouri and Christou*, 2000], implies that the noninternalized costs of the currently observed myopic groundwater extraction are significant. Thus benefits from optimally managing this resource could be nonnegligible, in contrast to the results from the ''Gisser-Sanchez effect'' literature [*Gisser and Sánchez*, 1980] reviewed by *Koundouri* [2004].

[28] Finally, in addition to the potential of this methodology as a demand management tool via pricing, technical inefficiency measures can be used by the regulator for competitive benchmarking (''yardstick competition'') in which taxes or subsidies granted to each farm are based on the costs of a similar (in terms of input mix) but more efficient firm. As indicated in the previous section of the paper, such a regulatory framework can increase managers incentives toward efficiency, an admittedly difficult task when regulation of common-pool resources is at stake. Moreover, implementing competitive benchmarking can potentially reduce the informational asymmetry between the farmers and the regulators, which is another major issue for the implementation of agricultural policies.

Appendix A: Data Sources and Definitions

[29] Data are drawn from three Production Surveys conducted in the agricultural region of Kiti, located in the Mediterranean island of Cyprus, in 1991, 1997, and 1999. Parcel-specific data includes: area of holding, land use and tenure, area planted, production of temporary and permanent crops, production inputs (including extracted groundwater), administrative costs, hydrogeological characteristics (i.e., head of the underlying aquifer), personal characteristics of buyers and sellers, employment of holders and family members, labor costs, value of construction works and other investments, indirect taxes and other expenses. The quality of the data-set is limited by the usual difficulties that one encounters when attempting to document inputs and outputs of agricultural activities. Particular difficulties where encountered in the collection of accurate groundwater extraction rates. Although groundwater extraction is metered in the area, the farmers in the area have a history of trying to under-report their extraction by manipulating the meters of their wells. The Cyprus Water Development Department, however, claims that farmers behavior is strictly monitored and data inaccurancies with respect to groundwater extraction should be limited. (Moreover, reported extraction rates were compared with crop-specific water requirements for each farm and found compatible.) For the interested reader the questionnaire used in these surveys is given by *Koundouri* [2000], together with the description of the collected information and constructed variables, as well as their descriptive statistics.

[30] In particular, the data-set is a balanced panel of the same 76 cross sections over the three years: 1991, 1997, and 1999. Output: y = firm-specific total value of output from production of agricultural crops, measured in Cyprus pounds (£1 Cyprus worth £1.14 UK) and deflated by the wholesale agricultural index. Inputs: x_1 = farm-specific total area of nonirrigated land (0.1 hectares), x_2 = farm-specific annual labor costs (Cyprus pounds), x_3 = farm-specific total value of input costs, including fertilizers, manure, pesticides, fuel and electric power for groundwater extraction (Cyprus pounds deflated by the wholesale agriculture price index), x_4= farm-specific yearly groundwater extraction (m^3), x_5 = farm-specific water table head (m), x_6 = farm-specific total area of irrigated land (0.1 hectares); the negative of x_6 is the dependent variable of the estimated stochastic frontier.

References

Aigner, D., C. A. K. Lovell, and P. J. Schmidt (1977), Formulation and estimation of stochastic frontier production function models, *J. Econ.*, *6*(1), 21–37.

Arrow, K., P. Dasgupta, and K.-G. Mäler (2003), Evaluating projects and assessing sustainable development in imperfect economies, *Resour. Energy Econ.*, *26*, 647–685.

Battese, G. E., and T. J. Coelli (1992), Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India, *J. Prod. Anal.*, *3*, 153–169.

Berck, P. (1995), Empirical consequences of the Hotelling Principle, in *The Handbook of Environmental Economics*, edited by D. Bromely, pp. 202 – 221, Blackwell, Malden, Mass.

Brock, W., and A. Xepapadeas (2004), Management of interacting species: Regulation under nonlinearities and hysteresis, *Resour. Energy Econ.*, in press.

Dasgupta, P. S., and K.-G. Mäler (2000), Net national product, wealth and social well-being, *Environ. Dev. Econ.*, *5*, 69–93.

Färe, R., and S. Grosskopf (1990), A distance function approach to measuring price efficiency, *J. Public Econ.*, *43*, 123–126.

Färe, R., and D. Primont (1995), *Multi-output Production and Duality: Theory and Applications*, Kluwer Acad., Norwell, Mass.

Färe, R., S. Grosskopf, C. A. K. Lovell, and S. Yaisawarng (1993), Derivation of shadow prices for undesirable outputs: A distance function approach, *Rev. Econ. Stat.*, *75*(2), 374–380.

Färe, R., S. Grosskopf, and C. A. K. Lovell (1994), *Production Frontiers*, Cambridge Univ. Press, New York.

Gisser, M., and D. A. Sánchez (1980), Competition versus optimal control in groundwater pumping, *Water Resour. Res.*, *16*, 638–642.

Grosskopf, S., and K. Hayes (1993), Local public sector bureaucrats and their input choices, *J. Urban Econ.*, *33*, 151–166.

Halvorsen, R., and T. R. Smith (1984), On measuring natural resource scarcity, *J. Polit. Econ.*, *92*(51), 954–964.

Halvorsen, R., and T. R. Smith (1991), Test of the theory of exhaustible resources, *Q. J. Econ.*, *106*, 123–140.

Howe, C. (2002), Policy issues and institutional impediments in the management of ground water: Lessons from case studies, *Environ. Dev. Econ.*, *7*, 625–642.

Koundouri, P. (2000), Three approaches to measuring natural resource scarcity: Theory and application to groundwater, Ph.D. thesis, Fac. of Econ. and Polit., Univ. of Cambridge, Cambridge, U. K.

Koundouri, P. (2003), Contrasting different methodologies to deriving natural resource scarcity rents, in *Economics of Water Management in Developing Countries: Problems, Principles and Policies*, edited by P. Koundouri et al., pp. 157 – 178, Edward Elgar, Northampton, Mass.

Koundouri, P. (2004), Potential for groundwater management: Gisser-Sanchez effect reconsidered, *Water Resour. Res.*, *40*, W06S16, doi:10.1029/2003WR002164.

Koundouri, P., and C. Christou (2000), Dynamic adaptation to resource scarcity with backstop availability, paper presented at the 10th Annual Conference, Eur. Assoc. of Environ. and Resour. Econ., Rethymnon, Greece, June.

Lau, L. J. (1976), A characterization of the normalized restricted profit function, *J. Econ. Theory*, *12*, 131–163.

Shephard, R. W. (1970), *Theory of Cost and Production Functions*, Princeton Univ. Press, Princeton, N. J.

P. Koundouri, Department of Economics, University of Reading, Reading, RG6 6AA, UK. (p.koundouri@reading.ac.uk)

A. Xepapadeas, Department of Economics, University of Crete, Rethymno 74 100, Greece. (xepapad@econ.soc.uoc.gr)