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Estimating Agricultural Pollution Abatement Costs at the Plot Level Using Experimental Data: A Maximum Entropy Approach

Craig A. Bond and Y. Hossein Farzin

This paper uses a directional output distance function to estimate a multi-output production frontier for a sample of experimental plots grown for the Sustainable Agriculture Farming Systems project at the University of California, Davis. Cross-sectional technical efficiency indices are estimated that take into account two proxies for undesirable output: number of trips across a field as a proxy for air pollution and/or soil erosion, and pints of pesticides applied to account for potential leaching and/or health risks. Shadow price estimates based on marginal rates of transformation ranged from \$8–\$21 for trips, while shadow prices for pints of pesticides averaged \$23–\$37.

Key words: directional distance function, environmental efficiency index, shadow price

Introduction

Agricultural economists and agronomists have long been interested in the response of crop outputs to various inputs in the production process in order to recommend optimal management practices based on marginal economic principles. Much of the attention has focused on crop response to directly applied marketable inputs, such as fertilizer and pesticides (see, e.g., Llewelyn and Featherstone, 1997; Frank, Beattie, and Embleton, 1990), with relationships estimated in a single-output, multiple-input empirical framework. Increasingly, however, the notion of the agricultural production system is being expanded to include not only directly marketable inputs and outputs, but also the effects of a given production system on the productivity and quality of the land, as well as the negative consequences of production on various aspects of environmental quality. Often, analyses of this broader system are conducted under the umbrella term "sustainable agriculture," which generally implies some interest in either off-farm effects, reduced agricultural inputs, or both.

Of specific interest are the implicit tradeoffs that can be (and, in fact, are) made between components of the broad resource system, especially with regard to management decisions. Since many of these tradeoffs are not manifested in the market, however, a

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convenient valuation statistic, such as a price, is not readily observable as it is with a marketable input or output. Thus it is necessary to use empirical techniques to estimate such shadow prices, which can subsequently be used to guide development of alternative production systems and/or policy. For example, an estimation of the expected marginal benefit of a nonmarketable desirable input, such as the shadow price of one unit of indigenous nitrogen in the soil, can aid in the design of optimal farm management practices in low-input agriculture, and these prices can be used as weights in a variety of cost-benefit analyses and valuation exercises, such as comparing production technologies or valuing land as a stock of natural capital. A (negative) shadow price for a non-desirable output, such as pesticide runoff, can be used to inform policy makers about the relative costs of pollution abatement. In the case of negative externalities, the predicted abatement costs can be used in developing price-based incentives (taxes and subsidies) to internalize the external costs of production agriculture (Koundouri and Xepapadeas, 2004).

In order to quantify several of these tradeoffs across alternative agricultural production systems, this paper employs a multi-output parametric directional distance function approach using experimental data from the Sustainable Agriculture Farming Systems (SAFS) plots at the University of California, Davis, over the period 2003–2005. In particular, we focus on the abatement costs associated with two potentially pollution-generating production activities: the number of mechanized trips across a field, which, among other things, generates air pollution; and the total quantity of pesticides (herbicides and fungicides) used in production, which has the potential to contaminate ground and surface water.[1,2]

Each of these elements of production are treated as undesirable outputs that are jointly produced with marketable crop yields, and the ratio of the derivatives of the estimated distance function indicates the marginal rate of transformation between the undesirable and desirable elements of the expanded production system. A normalization allows for recovery of the appropriate shadow prices, and thus the marginal abatement costs for each observation in the sample (Färe and Grosskopf, 1990, 1998; Färe et al., 1993). In addition, the distance function approach can lend insights into the nature of the substitutability properties between nonmarketable and marketable inputs and outputs in a multivariate setting, as well as estimating the relative efficiency of various production systems (Paul and Nehring, 2005; Murillo-Zamorano, 2004). This relative efficiency, and the efficiency rankings between systems, is shown to be sensitive to the inclusion of environmental outputs.

This paper contributes to the literature in a number of ways. First, to our knowledge, it is the first application of the directional distance function to micro-level agricultural data. Previous studies have used the more specific Shephard distance function that only allows for proportional changes in all outputs or inputs, regardless of the nature of that input or output (Färe et al., 2005). Second, in contrast to studies using aggregated regional- or national-level time-series agricultural data in order to estimate relative

[1] Ideally, a direct measure of pollution would be used in the analysis. However, as this information was not available, these measures are used as proxies for undesirable outputs.

[2] This study originally intended to include nonmarketable inputs (soil quality indicators) as well. However, incompatibility between soil data across the three years of the study period precluded inclusion at this time. Of course, the distance function methodology is well suited for analysis of this sort, and the techniques contained herein can easily be adapted for multiple marketable and nonmarketable inputs.

technical efficiencies and shadow prices over time, we focus on a cross-section of alternative cropping systems at the micro level, based on experimental data. Finally, we illustrate the use of generalized maximum entropy (GME) as an estimation technique that allows for imposition of theoretically consistent monotonicity constraints in a stochastic framework, rather than the deterministic approach of Aigner and Chu (1968) that has been used in other empirical work (see, e.g., Färe et al., 2005; Hailu and Veeman, 2000).

The Distance Function Methodology

Originally introduced by Shephard (1970), an output or input distance function essentially measures the efficiency of a production point relative to the production frontier, and represents a complete characterization of any production technology so long as free disposability of positively valued outputs or inputs is assumed (Färe and Grosskopf, 1996).[3] Utilizing duality results from production theory and assuming that at least one observed output or input price equals its accounting price, the shadow prices of the nonmarketable input and output commodities can be recovered (Färe et al., 1993; Färe and Grosskopf, 1990, 1998). A major advantage of this approach is that it does not rely on maintained behavioral assumptions of profit maximization or cost minimization with respect to market prices, and thus the method is appropriate for experimental data (Färe, Grosskopf, and Nelson, 1990). Shephard's distance function assumes proportional expansion (contraction) of all outputs (inputs), and is a special case of the directional distance function model of technology presented below.

In practice, the literature has tended to focus on undesirable outputs, with examples including shadow pricing of water pollution from paper and pulp mills (Färe et al., 1993; Hailu and Veeman, 2000), air pollution from electricity production (Lee, Park, and Kim, 2002; Färe et al., 2005), and excess nitrogen from production agriculture (Shaik, Helmers, and Langemeier, 2002). On the input side, Koundouri and Xepapadeas (2004) estimated the shadow price of common property groundwater for use in irrigated agriculture, while Piot-Lepetit and Vermersch (1998) computed the shadow price of organic nitrogen in the French pig sector. Interestingly, Jaenicke and Lengnick (1999) and Jaenicke (2000) use distance functions in an agricultural setting to estimate a soil-quality index and the effect of crop rotations on productivity growth, respectively, but do not report shadow values for the nonmarketable inputs.

In brief, the directional (output) distance function is a univariate measure of the distance between a given production point (in multivariate space) and the technologically efficient production frontier (Chambers, Chung, and Färe, 1998; Färe et al., 2005). Assuming certain convexity, closure, and disposability axioms on the set of all possible outputs (documented in Färe et al., 2005), this function is a complete representation of the production technology, and provides a natural estimate of the relative efficiency of each observation. A major advantage of this approach over more traditional production function methodologies is the ability to represent multiple, or joint, outputs, some of which may be negatively valued by producers and/or society (i.e., "bads").

[3] Free disposability implies that if an input vector is a member of the technically feasible output set, then a proportional scaling up of this input vector is also a member of this same set (see, e.g., Hailu and Veeman, 2000, p. 256). Similarly, for an output vector, a proportional scaling down of the vector is a member of the set.

Mathematically, the directional output distance function is defined as:

$$D_i^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; g_y, -g_z) = \sup\{\phi_i > 0: (\mathbf{y}_i + \phi_i g_y, \mathbf{z}_i - \phi_i g_z) \in L_i(\mathbf{x}_i)\},$$

where for each observation i, $\mathbf{y} \in \Re_+^N$ is a vector of positively valued farm outputs (e.g., crops or livestock biomass), $\mathbf{z} \in \Re_+^M$ is a vector of negatively valued farm outputs (e.g., air or water pollution) that cannot be freely disposed, $\mathbf{x} \in \Re_+^J$ is a vector of farm inputs, and ϕ_i represents the maximum proportional expansion of good outputs $\mathbf{y}_i$ in the vector direction g_y and the maximum contraction of bad outputs $\mathbf{z}_i$ in the g_z direction that could be produced with the identical input vector $\mathbf{x}_i$. $L(\mathbf{x})$ is the aforementioned set of all possible outputs that can be produced by the input vector $\mathbf{x}$. Points on the production frontier are defined by the property $D_i^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; g_y, -g_z) = 0$, such that there is no feasible proportional expansion of goods and bads in the direction $(g_y, -g_z)$. In addition, the directional output distance function is nonincreasing in desirable outputs and nondecreasing in undesirable inputs, concave in all feasible outputs, and satisfies the translation property, defined by

$$D_i^O(\mathbf{x}_i, \mathbf{y}_i + \theta g_y, \mathbf{z}_i - \theta g_z; g_y, -g_z) = D_i^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; g_y, -g_z) - \theta, \quad \theta \in \Re.$$

Shadow prices $\mathbf{p}_y$ and $\mathbf{p}_z$ are introduced through the revenue function:

$$R_i(\mathbf{x}_i, \mathbf{p}_y, \mathbf{p}_z) = \max_{\mathbf{y}_i, \mathbf{z}_i}\{\mathbf{p}_y\mathbf{y}_i + \mathbf{p}_z\mathbf{z}_i: D_i^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; g_y, -g_z) \geq 0\}.$$

Assuming that the observed price of a marketable input or output (say p_{y^1}) is equal to the true shadow price in the revenue function,[4] the observation-specific shadow prices (or marginal abatement costs) of undesirable outputs can be recovered through the following equation:

$$(1) \qquad p_{z_i^n} = -p_{y_i^1} \frac{\partial D_i^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; g_y, -g_z)/\partial z_i^n}{\partial D_i^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; g_y, -g_z)/\partial y_i^1}.$$

Note that the relative abatement cost, or shadow price, of an undesirable output is equal to the marginal rate of transformation between outputs along the production surface, and as such provides the marginal opportunity cost of reducing that output. For a more detailed exposition of the directional distance function, the reader is referred to Chambers, Chung, and Färe (1998) and Färe et al. (2005). For a corresponding discussion of Shephard's radial output and input distance functions and derivation of the shadow price equations, the reader is referred to Färe, Grosskopf, and Nelson (1990) and Hailu and Veeman (2000).

Estimation of Distance Functions

Output distance functions (or their value) can be estimated in a number of ways, broadly characterized into parametric and nonparametric techniques, and deterministic and stochastic specifications. Nonparametric methods are typically classified as Data

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[4] Färe and Grosskopf (1990) also note that a balanced budget or not-for-profit assumption can be used for identification purposes.

Envelopment Analysis (DEA), are generally deterministic, tend to be radial, or non-directional, in nature, and result in a nondifferentiable production possibility set consisting of the convex hull of all the observed input-output vectors in the sample, with the outermost observations defining the production frontier surface in a piecewise linear fashion (Murillo-Zamorano, 2004; Färe and Grosskopf, 1996). Imposing additional structure on the distance function through a specific differential functional form, say $D_i^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; g_y, -g_z) = f(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \boldsymbol{\beta}, g_y, -g_z)$, where $\boldsymbol{\beta}$ is a vector of parameters to be computed and $f(\cdot)$ satisfies the proper theoretical translation, monotonicity, and symmetry properties, allows the derivatives in (1) to be easily computed, and allows for directions to be explicitly specified.[5]

The parameter vector can be recovered either deterministically through nonlinear programming, as in Aigner and Chu (1968), or through econometric estimation via imposition of a compound error term. The deterministic recovery process envelops all of the data and does not allow for statistical noise or measurement error, which is conceptually unappealing from an econometric standpoint (Ruggiero, 1999; Ondrich and Ruggiero, 2001). On the other hand, this approach has several advantages. First, the theoretically desirable properties of the distance function can be imposed directly via constraints on the programming problem, which is especially important in the case of the monotonicity properties of the derivatives of the distance function with respect to desirable and undesirable inputs (Hailu and Veeman, 2000). These take the form of inequality constraints, which can be problematic in a standard econometric framework. Second, finite sample performance, at least with respect to rank correlations between estimated and true efficiency measures, has been shown to be superior using deterministic methods rather than stochastic specifications (Ruggiero, 1999).[6] Finally, this technique is feasible for smaller, ill-behaved samples while maintaining the advantage of differentiability of the distance function (Färe et al., 1993). However, even the large amount of a priori information imposed in the form of homogeneity, monotonicity, and symmetry constraints may not be sufficient to adequately locate the reference technology, especially if the problem is ill-posed due to a paucity of data.

An alternative to deterministic specifications is to assume a compound error stochastic specification, in which deviations from the frontier can take the form of either inefficiency or statistical noise/measurement error. Developed by Aigner, Lovell, and Schmidt (1977), with firm-specific efficiency estimates provided by Jondrow et al. (1982), the approach develops the estimating equation by exploiting particular properties of the function to be estimated: homogeneity in the context of radial distance functions, translation in the case of directional distance functions. In the context presented here, each observation can be identified relative to the technology frontier through

$$f\left(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \boldsymbol{\beta}, g_y, -g_z\right) + \varepsilon_i = 0, \tag{2}$$

where ε_i is a random disturbance term such that $\varepsilon_i = v_i - u_i$, $u_i \geq 0$ is an i.i.d. random variable with positive support and finite variance representing deviations from the

[5] Although the function $f(\cdot)$ may not explicitly depend on g_y and g_z, the parameter vector $\boldsymbol{\beta}$ may depend on these values.

[6] Ruggiero (1999) used Monte Carlo analysis to compare efficiency estimates from cross-sectional deterministic and stochastic parametric specifications for radial distance functions to the true data-generating process in a single-output frontier model, and found that "the parametric deterministic model outperformed the stochastic frontier model in nearly all of the model situations considered" (p. 562). Rather than a linear programming approach, however, the authors used a corrected OLS procedure to estimate parameter values. Greene (1993) has the details.

production frontier surface (in other words, the negative of the distance function), $v_i \sim$ i.i.d. $(0, \sigma_v^2)$ is white noise, and u_i and v_i are assumed independent (Murillo-Zamorano, 2004; Paul and Nehring, 2005; Koundouri and Xepapadeas, 2004). To obtain variation on the right-hand side of (2) for estimation, the translation property is exploited such that:

$$(3) \qquad -\theta_i = f\left(\mathbf{x}_i, \mathbf{y}_i + g_y\theta_i, \mathbf{z}_i - g_z\theta_i; \boldsymbol{\beta}, g_y, -g_z\right) + \varepsilon_i .$$

Depending on the distributional assumptions the researcher is willing to make concerning the compound error terms, there are a number of ways to estimate (3), including maximum likelihood, generalized method of moments, or even ordinary least squares.[7]

However, as Ondrich and Ruggiero (2001) show, identification of firm-specific inefficiencies [as identified by $f_i(\cdot)$ or u_i] are dependent on these distributional assumptions, and no absolute measure of inefficiency can be calculated, despite the conceptually appealing treatment of noise. Thus, the stochastic specification may, in empirical practice, offer little or no advantage over deterministic models. Furthermore, these methods of estimation are not conducive to application of monotonicity constraints on good and bad outputs (or inputs), and unconstrained estimation may result in an estimated output distance function that is not consistent with theory.

Finally, these estimation techniques are subject to the same data constraints common to all traditional econometrics—namely, the existence of a sufficient number of degrees of freedom in order to uniquely and consistently identify the parameters of the presumed input distance function and a lack of severe multicollinearlity (or alternatively stated, a well-conditioned problem that is not ill-posed). In many applications, such as the numerous studies cited here, these may not be significant issues; yet in others they may be quite constraining, due to a large number of parameters to be estimated (a consequence of the necessity of a flexible functional form), a lack of data or the very nature of the data, or most likely, all of the above. This may be especially true in the case of replicated experimental data common in agronomic and other agricultural applications, which are characterized by multiple observations of output resulting from identical input vectors on different plots, reducing data variability in the explanatory variables and severely limiting the power of traditional estimation techniques.

Recently, the technique of Generalized Maximum Entropy (GME) estimation has been developed to overcome many of these difficulties. GME assumes a discrete probability distribution for each of the K parameters to be estimated and each of the I disturbances in the sample, and then maximizes the sum of the entropies for each of these distributions, subject to the data, in order to uniquely determine the conditional expectation of each of the unknowns. As such, it can be used to identify ill-posed and severely ill-conditioned econometric problems, as well as impose the theoretically consistent inequality and monotonicity constraints on the parameter vector. In this sense, GME is the natural stochastic analog to the deterministic approach advocated by Aigner and Chu (1968). For a more detailed explanation of GME estimation, the reader is referred to the seminal works of Golan, Judge, and Miller (1996), Paris and Howitt (1998), and Fraser (2000), and for an efficiency application, Lansink, Silva, and Stefanou (2001).

[7] Estimates of the slope coefficients are unbiased and consistent using OLS estimation, but the intercept term requires adjustment as the error term has a nonzero mean (Greene, 2000).

Data

The data for this paper are taken from the newest phase of the Sustainable Agriculture Farming Systems (SAFS) project at the Russell Ranch location (lat. 38° 32′N, long. 121° 47′W, 18 m elevation) at the University of California, Davis. The SAFS project is a long-term interdisciplinary study designed to collect data on various traditional and non-traditional characteristics of agricultural systems, including, but not limited to, environmental quality, food safety, alternative production systems, resource conservation, and soil quality (SAFS, 2004). The newest phase began during the 2003 growing system, with research geared toward comparing three alternative production systems (conventional, low-input, and organic) in a two-year rotation of processing tomatoes followed by field corn using furrowed irrigation. In addition, each production system was managed using standard and reduced tillage, for a total of six distinct production systems for each crop with three replications of each. To date, three years of data are available. Located in the Sacramento Valley, the climate can be classified as Mediterranean, with 400–500 mm annual rainfall occurring primarily in the winter months, and mean daytime temperatures during the growing season of 30–35°C (SAFS, 2004).

Plots for each system were managed as follows: conventional systems according to standard practice in the Sacramento Valley, organic systems according to best management organic practices and materials, and low-input using a winter legume cover crop (vetch and Australian winter pea) to fertilize and add organic material to the soil (SAFS, 2004).[8] Tillage regimes were designed to mimic conventional practice for the standard tillage treatments, while the conservation tillage experiment attempted to minimize the number of trips across a field without sacrificing yields (SAFS, 2004). Note that the behavioral assumption of profit maximization is not maintained with these experimental data. (Additional information about the SAFS project and related activities can be found at http://safs.ucdavis.edu/.)

Estimation of the directional output distance functions requires information on inputs and outputs (both desirable and undesirable). In order to conserve degrees of freedom in the estimation process, multilateral Fisher quantity indices (also known as EKS indices) for desirable outputs and inputs were constructed over the entire 36-observation sample, using the observation for conventional standard-tillage corn as the baseline. Similar index approaches have been used in the literature for time-series data (see, e.g., Shaik, Helmers, and Langemeier, 2002). A multilateral Fisher quantity index of observation k relative to baseline observation l is defined as a function of the ratios of bilateral Fisher quantity indices, or

$$(4) \qquad F_{k,l}^{ML} = \prod_{i=1}^{36} \left(\frac{F^{BL}(\mathbf{p}^i, \mathbf{p}^k, \mathbf{q}^i, \mathbf{q}^k)}{F^{BL}(\mathbf{p}^i, \mathbf{p}^l, \mathbf{q}^i, \mathbf{q}^l)} \right)^{1/36},$$

where $\mathbf{p}^i$ is the price vector for the ith observation (in 2005 dollars), $\mathbf{q}^i$ is the corresponding quantity vector, and F_{BL} is the bilateral Fisher quantity index between two observations (Fox, 2003). Specifically, taking the numerator in (4) as representative,

[8] The organic system utilized the same cover crop as the low-input system for both corn and processing tomatoes.

$$F^{BL}(\mathbf{p}^i, \mathbf{p}^k, \mathbf{q}^i, \mathbf{q}^k) = \left(\frac{\sum_j p_j^i q_j^k}{\sum_j p_j^i q_j^i} \cdot \frac{\sum_j p_j^k q_j^k}{\sum_j p_j^k q_j^i} \right)^{1/2},$$

with the index j representing the elements of the price and quantity vectors.

In the application here, desirable outputs are simply yields of the crop per acre, with prices reflecting market conditions at the time of harvest and, in the case of organic crops, any price premium. Inputs are measured as total expenditures on 11 operating cost categories: ground preparation, cover crop expenditures, weed control, planting, irrigation, fertilizer, insect control, disease control, harvest, residue management, and interest on capital. Unfortunately, collected soil quality data were incomplete and not comparable between years, so there are no nonmarketable input data available. Data were generated by U.C. Davis Cooperative Extension by taking the operational schedule from each experimental plot and running a budget plan for an assumed representative farm.

Ideally, direct measures of undesirable outputs would be included in the analysis, though such data are notoriously difficult and expensive to obtain. For example, a component of the SAFS project is to measure the quantity and quality of runoff for each system during the winter season; unfortunately, the selected measurement system was relatively unsuccessful during the first two years of the experiment, resulting in data of questionable quality. As such, it is not included in the analysis here. Rather, we choose to utilize proxy measures that are likely to be correlated with pollution and are of particular interest to the SAFS project.[9]

Thus, two proxy variables are chosen: (*a*) the total number of trips across a field, which affects, among other things, air pollution; and (*b*) the total quantity, in pints, of pesticides (herbicides and fungicides) applied, which can affect food safety and water quality (SAFS, 2004). While there are obvious conceptual difficulties with each of these variables representing pollution per se, recall that the shadow price calculations represent the marginal cost, in terms of desirable output foregone, of reducing whatever measure of undesirable output is used. Thus, for policy purposes, this information can be used in analyses of the costs of changing *management* practices associated with pollution, although valuation of the costs and/or benefits of reducing pollution itself may, in fact, differ. One interpretation might be that the undesirable output produced is directly proportional to the proxy measure used to represent it. A summary of the data can be found in table 1.

Functional Forms and Assumptions

A quadratic functional form is used in the analysis, with $g_y = 1$ and $g_z = 1$. As noted in Färe et al. (2005), this choice of directional vector allows for increases in good outputs and decreases in bad outputs along a 45° vector from the origin, and allows for aggregation to the industry level if such data were available. Furthermore, the quadratic

[9] For example, Shaik, Helmers, and Langemeier (2002) use calculated nitrogen surplus from a mass-balance approach as their pollution output variable in the absence of observing actual nitrate contamination statewide over time. This proxy was validated through regression of a set of nitrate contamination data (not appropriate for use in the shadow price calculations) on similar excess nitrogen calculations, with positive and significant correlation verified.

Table 1. Description of Variables and Summary Statistics

Variable	Description	Mean	Standard Deviation	Minimum	Maximum
x	Input Index	2.07	1.22	0.66	5.32
y	Output Index	1.59	1.09	0.15	3.58
z_1	Number of Trips	22.22	6.90	9.00	37.00
z_2	Pints of Pesticide	3.95	3.61	0.00	10.67
D_{2004}	Dummy 2004	0.33	0.48	0.00	1.00
D_{2005}	Dummy 2005	0.33	0.48	0.00	1.00
D_{Corn}	Dummy Corn	0.50	0.51	0.00	1.00
P_y	Output Index Price [a]	565.33	120.92	467.50	942.08

[a] Prices are in 2005 \$.

functional form is easily restricted to satisfy the translation property, despite being a flexible second-order approximation to an unknown function.

Specifically, in the context here with one desirable output and one input (in index form), and two undesirable outputs, the directional distance function is specified as follows:

$$
\begin{aligned}
(5) \qquad D_i^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; 1, -1) &= \alpha_0 + \alpha_1 y_i + \beta_1 x_i + \sum_{j=1}^{2} \gamma_j z_{ji} + \tfrac{1}{2}\alpha_2 y_i^2 + \tfrac{1}{2}\beta_2 x_i^2 \\
&+ \tfrac{1}{2}\sum_{j=1}^{2}\sum_{j'=1} \gamma_{j,j'} z_{ji} z_{j'i} + \mu y_i x_i + \sum_{j=1}^{2} \eta_j y_i z_{ji} \\
&+ \sum_{j=1}^{2} \rho_j x_i z_{ji} + \delta_1 D_{2004} + \delta_2 D_{2005} + \delta_3 D_{Corn} \\
&= f(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \mu, \boldsymbol{\eta}, \boldsymbol{\rho}, \boldsymbol{\delta}, 1, -1),
\end{aligned}
$$

where y_i, z_{ji}, and x_i are the desirable output index, the jth undesirable output, and the input quantity index for the ith observation, respectively; D_{year} are dummy variables for 2004 and 2005 growing seasons; and D_{Corn} is a dummy variable equal to one if the crop grown is corn. In addition, the following restrictions are placed on the parameters to satisfy the translation property and symmetry restrictions:

$$
\begin{aligned}
&\alpha_1 - \sum_{j=1}^{2}\gamma_j = -1, \quad \alpha_2 - \sum_{j=1}^{2}\eta_j = 0, \quad \gamma_{11} + \gamma_{12} - \eta_1 = 0, \quad \gamma_{21} + \gamma_{22} - \eta_2 = 0, \\
&\tfrac{1}{2}\alpha_2 + \tfrac{1}{2}\left(\gamma_{11} + \tfrac{1}{2}\gamma_{12} + \gamma_{22}\right) - \sum_{j=1}^{2}\eta_j = 0, \quad \mu - \sum_{j=1}^{2}\rho_j = 0, \\
&\gamma_{j,j'} = \gamma_{j',j}, \quad j, j' = 1, 2.
\end{aligned}
$$

Equation (5) is estimated using both traditional econometric methods (OLS) and GME by appending a compound error term and setting θ_i equal to the desirable output index as in (3), then estimating this function at the transformed output variables. For GME estimation, each parameter is parameterized with five discrete support points:

[−50, −25, 0, 25, 50] for the intercept term α_0 and [−5, −2.5, 0, 2.5, 5] for each of the slope and dummy parameters. Each error term is assumed to have support [−4, −2, 0, 2, 4].[10]

Note, however, that as written, the composed error term in (3) has a nonzero mean given the strictly nonnegative support for u_i, but the support for the composed error term as a whole extends into the negative region. As in OLS estimation, this causes little problem, since conceptually the data can be transformed to renormalize around zero (see, e.g., Greene, 2000).[11] As such, the model retains the zero mean error assumption of the classical linear regression model, and slope parameters are unbiased and consistent as in Golan, Judge, and Miller (1996). Because the intercept term does not enter the calculation of shadow prices, the inconsistency of this parameter is of little consequence for these calculations.

To check for theoretical consistency associated with the monotonicity conditions with respect to each output, OLS estimation proceeds without any additional restrictions on the parameter values. In the GME maximization problem, however, we directly impose, through inequality constraints on the proper functions, the monotonicity conditions with respect to desirable outputs (the output quantity index) and undesirable outputs (number of trips and quantity of pesticides).

One final concern is the inability to identify the value of the distance function, as it enters additively with the statistical noise term. In previous practice, particular distributions are assumed for each of the error terms, and the sufficient statistics for these distributions can be used to estimate expected values of the observation-specific inefficiency terms conditional on the value of the estimated composed error (Jondrow et al., 1982). Because such distributions are not assumed under the GME framework, this approach is not possible here. We therefore rely on the previously discussed results of Ondrich and Ruggiero (2001) and Ruggiero (1999), and use corrected OLS by adding the maximum error term, as defined in (2), to the estimated intercept in (5):

$$\tilde{\alpha}_0 = \alpha_0 + \max(\varepsilon_i).$$

The reader is reminded that the resulting distance function measure is relative to the most efficient observation in the sample. OLS estimation was performed using Intercooled STATA 7.0, while GME estimation was conducted in the GAMS programming language with the MINOS2 solver.[12]

Results and Discussion

Technical Efficiency Excluding Environmental Considerations

Before estimating the shadow prices of the undesirable outputs, we first examine the estimated values of a total factor productivity (TFP) index, which compares the technical efficiency of each production system/tillage treatment by year, arbitrarily using one of

[10] See table 1 for sample standard deviations of the dependent variable. The supports for the error encompass the three sigma rule, while the other parameter supports were based on a priori expectation and testing for robustness. The wider support on the intercept term is imposed based on the results of Fraser (2000), who found that the intercept was sensitive to the support interval. This seems especially relevant given the expected nonzero mean on the error term ε_i.

[11] Transforming the data such that the vector of ones associated with the constant term is equal to one plus the mean of the composed errors results in a model with an error term with expected mean zero.

[12] Code is available from the authors upon request.

Table 2. Economic Total Factor Productivity (TFP) Relative to Conventional Standard Tillage Corn, 2003, by Production System (baseline = 1)

Description	Total	Corn	Tomatoes
All	0.776 (0.397)	0.674 (0.463)	0.878 (0.297)
Standard Tillage (ST)	0.756 (0.361)	0.567 (0.361)	0.944 (0.259)
Conservation Tillage (CT)	0.797 (0.440)	0.781 (0.548)	0.813 (0.332)
Conventional (Conv)	1.138 (0.320)	1.248 (0.258)	1.027 (0.360)
Organic (Org)	0.550 (0.308)	0.316 (0.171)	0.783 (0.222)
Winter Legume Cover Crop (WLCC)	0.641 (0.293)	0.457 (0.167)	0.826 (0.282)

Note: Values in parentheses are standard errors.

the observations as the baseline. The TFP index is defined as the ratio between the output and input quantity indices for each observation, with the baseline normalized to a value of one. As such, those observations with a TFP index greater (less) than one are more (less) efficient than the baseline. The TFP index does not take into account environmental performance, but rather the ratio of aggregate desirable output to aggregate input, and can be considered representative of the interests of the producer, rather than society as a whole.

Table 2 summarizes the results by production system, assuming that the standard-tillage corn observation for 2003 is the baseline, with a TFP index of one. Any TFP index greater than one indicates the possibility of producing more output for the same level of inputs; i.e., the system is more technically efficient. Taking into account both crops and both tillage regimes, the "Total" column in table 2 shows that conventional systems (Conv) are most efficient, and organic systems (Org) are slightly less efficient than winter-legume cover cropped systems (WLCC). This general pattern remains consistent when individual crops are analyzed (columns 3 and 4), although the loss in efficiency when moving away from a conventional system in corn is greater than that for tomatoes. In contrast, there is little difference between standard tillage (ST) and reduced, or conservation, tillage (CT) overall. By crop, however, conservation tillage is most efficient for corn, but standard tillage is most efficient for tomatoes. These results highlight the potential heterogeneous impacts of alternative production systems on various crops, suggesting that generalizations about the relative efficiencies of various technologies should be made with caution.

The TFP analysis does not take into account any potential environmental externalities generated through agricultural production that may be negatively valued by society as a whole, and thus provides no guidance as to the social desirability of these alternative production practices. The value of the directional distance function described in (5) takes environmental considerations into account, as it provides a measure of efficiency that incorporates maximum possible expansion of the desirable output *and* maximum possible contraction of the undesirable outputs (proxied here by trips and pints of herbicides) in the $(g_y, -g_z) = (1, -1)$ vector direction, so that both greater yields

Table 3. Ordinary Least Squares (OLS) and Generalized Maximum Entropy (GME) Coefficient Estimates, Quadratic Functional Form

Variable	Coefficient	OLS	GME	Variable	Coefficient	OLS	GME
Constant (uncorrected)	α_0	5.540** (1.224)	0.898	$(z_2)^2$	γ_{22}	0.005* (0.003)	0.001
Y	α_1	-1.059** (0.091)	-0.836	Yx	μ	-0.079** (0.023)	-0.021
X	β_1	-0.847 (0.713)	0.327	yz_1	η_1	0.016 (0.012)	-0.004
z_1	γ_1	-0.038 (0.078)	0.157	yz_2	η_2	0.005* (0.003)	-0.001
z_2	γ_2	-0.021 (0.058)	0.008	xz_1	ρ_1	-0.028 (0.019)	-0.019
y^2	α_2	0.541** (0.213)	-0.005	xz_2	ρ_2	-0.051** (0.018)	-0.002
x^2	β_2	0.541** (0.213)	-0.042	D_{2004}	δ_1	0.110 (0.154)	0.218
$(z_1)^2$	γ_{11}	0.016 (0.012)	-0.002	D_{2005}	δ_2	0.102 (0.171)	0.406
z_1z_2	γ_{12}	0.000 (0.000)	-0.002	D_{Corn}	δ_3	-4.083** (0.693)	-1.407

Notes: Single and double asterisks (*) denote statistical significance at the 10% and 5% levels, respectively. Values in parentheses are standard errors.

and fewer trips and herbicides are taken into account (Färe et al., 2005). Consequently, it provides a convenient summary measure of economic/environmental efficiency in a compact, univariate form. Furthermore, the use of GME estimation allows for simple imposition of the theoretically consistent monotonicity conditions on positively and negatively valued outputs. Coefficient estimates from the GME estimation procedure are reported in table 3, along with the OLS analog for comparison purposes. In what follows, we restrict attention to the theoretically consistent GME results.

Table 4 reports the directional distance function values obtained from GME estimation with all relevant theoretical constraints imposed. Recall that the distance function value must be nonnegative and bound from below at zero, so that a lower distance function value implies greater efficiency, with a value of zero indicating production along the frontier. As can be seen in the "Total" column of table 4, conventional production is still most efficient across all crops and tillage regimes, but the lack of pesticide application in the organic system is taken into account, thus moving it ahead of cover-cropped systems in the ordinal efficiency rankings. This pattern is again maintained for individual crops, although the very small differences between conventional and organic production measures for tomatoes is worth noting as reductions in pesticide use do not appear to significantly affect the combined economic/environmental efficiency measure. Credit for reducing trips across the field with this combined measure results in conservation tillage systems ranked more efficient than standard tillage regimes in aggregate and for each crop individually.

A clearer picture of the differences between the TFP measures and the distance function measures of efficiency can be found in table 5, which ranks the combined production/tillage systems by crop from the most to least efficient. For corn, the top two

Table 4. GME Distance Function Estimates Relative to Most Efficient Observation, by Production System (most efficient = 0)

Description	Total	Corn	Tomatoes
All	0.790 (0.385)	0.841 (0.356)	0.738 (0.415)
Standard Tillage (ST)	0.823 (0.372)	0.897 (0.306)	0.749 (0.433)
Conservation Tillage (CT)	0.757 (0.405)	0.786 (0.411)	0.727 (0.422)
Conventional (Conv)	0.572 (0.315)	0.566 (0.148)	0.579 (0.444)
Organic (Org)	0.692 (0.328)	0.803 (0.398)	0.582 (0.221)
Winter Legume Cover Crop (WLCC)	1.104 (0.308)	1.155 (0.202)	1.053 (0.402)

Note: Values in parentheses are standard errors.

Table 5. Economic (Total Factor Productivity) and Combined (Distance Function) Efficiency Ordinal Rankings by Production System, Most to Least Efficient

Total Factor Productivity Efficiency Measure			Distance Function Efficiency Measure		
Crop/ Rank	Production System	TFP Score	Crop/ Rank	Production System	Distance Function Score
Corn:			***Corn:***		
1	Conventional CT	1.48	1	Conventional CT	0.48
2	Conventional ST	1.02	2	Conventional ST	0.66
3	Winter Legume Cover Crop CT	0.51	3	Organic CT	0.67
4	Winter Legume Cover Crop ST	0.40	4	Organic ST	0.94
5	Organic CT	0.35	5	Winter Legume Cover Crop ST	1.10
6	Organic ST	0.28	6	Winter Legume Cover Crop CT	1.21
Tomatoes:			***Tomatoes:***		
1	Conventional ST	1.07	1	Organic ST	0.52
2	Conventional CT	0.99	2	Conventional CT	0.54
3	Organic ST	0.93	3	Conventional ST	0.62
4	Winter Legume Cover Crop ST	0.83	4	Organic CT	0.65
5	Winter Legume Cover Crop CT	0.82	5	Winter Legume Cover Crop CT	1.00
6	Organic CT	0.63	6	Winter Legume Cover Crop ST	1.11

Note: CT = Conservation Tillage, ST = Standard Tillage.

most efficient production systems remain unchanged with the inclusion of the pollutant proxies (Conv CT and Conv ST), but the organic systems move into third and fourth place once the undesirable outputs are included. These findings suggest that the yield component in the efficiency computation dominates the environmental considerations for corn. For tomatoes, the reordering is even more dramatic, as the TFP-leading Conv ST system switches places with the third place Org ST structure once undesirable inputs are included, the Org CT technology increases from last to fourth place, and the WLCC systems once again drop to the fifth and sixth positions.

Clearly, then, incorporation of environmental considerations into the efficiency analysis has the potential to change both the qualitative and quantitative classifications of each of the production regimes by crediting the "production" of environmental quality rather than simply crop yields (Hailu and Veeman, 2000). From a policy standpoint, the results reported in table 5 provide information about "best practice" production systems that offer simultaneously the most output with the least environmental impact. In the case of corn, there is little compelling evidence to suggest that nonconventional production systems should be promoted (say, through policy instruments) on environmental grounds. In contrast, for tomatoes it appears that organic production systems have the potential to increase environmental quality while simultaneously increasing our measure of output. Cover cropping appears to fare the worst in terms of technical efficiency; however, we have not included a proxy for pollution resultant from fertilizer, which could change the results. Of course, profitability concerns of individual growers (including the costs of potentially switching to a new system) are likely to dominate production choice decisions.

Shadow Prices of Undesirable Output Proxy Variables

We next use the model results to estimate the shadow prices, or marginal abatement costs, of each of the proxies of nondesirable inputs using the formula in (1). As the desirable output for both corn and tomatoes is measured in terms of the multilateral Fisher output quantity index defined in (4), we use the implicit price defined by

$$p_{y_1^i} = \frac{TR_i}{F_{i,l}^{ML}},$$

where TR_i is total revenue for observation i and $F_{i,l}^{ML}$ is the output quantity index, relative to the Corn Conv ST observation in 2003, to normalize the shadow prices in 2005 dollars. The shadow price represents the marginal cost, in terms of the desirable input foregone, of reducing the proxy measure by one unit (pint in the case of herbicides, trip in the case of the tillage measure); alternatively, it can be interpreted as the value of desirable output the producer would gain if the proxy variable increased by one unit. This latter interpretation is helpful for those observations that have zero pesticide applications.

Summary statistics of the estimated shadow prices for both number of trips across the field and pints of pesticides for each observation measure are presented in table 6. Recall these prices are calculated at the projected efficient point in the direction of $(g_y, -g_z) = (1, -1)$ (Färe et al., 2005). As in other studies (e.g., Färe et al., 1993; Hailu and Veeman, 2000), the prices are quite variable across production technologies and crops, representing the differences in output mix at each point. Furthermore, imposition of the monotonicity assumptions affects the results. Under OLS estimation, 21 of 36 shadow prices for number of trips are nonnegative (in accordance with the theory), while 18 of 36 observations are nonnegative for the herbicide proxy. For the GME estimation which imposes this constraint, 34 of 36 of the shadow prices for trips and herbicides are strictly positive.

As can be seen in table 6, the average GME shadow price estimates overall are \$37 per pint of herbicide and \$8 per trip across the field, although they range from \$0 to \$91 for the former and \$0 to \$26 for the latter. In other words, on average for these data, the

Table 6. Estimated Shadow Prices of Undesirable Outputs by Crop, 2005 $

	Total		Corn		Tomatoes	
Description	Herbicide	Trip	Herbicide	Trip	Herbicide	Trip
All	37.28	8.40	58.74	10.13	15.83	6.67
	(26.54)	(6.68)	(18.43)	(7.12)	(11.63)	(5.90)
Standard Tillage (ST)	32.84	10.80	51.95	13.34	13.74	8.27
	(24.27)	(7.38)	(18.21)	(7.08)	(9.96)	(7.15)
Conservation Tillage (CT)	41.72	6.00	65.53	6.93	17.92	5.07
	(28.61)	(5.01)	(16.83)	(5.86)	(13.36)	(4.13)
Conventional (Conv)	31.52	4.00	48.30	5.85	14.73	2.15
	(20.64)	(3.42)	(12.87)	(3.39)	(9.75)	(2.46)
Organic (Org)	50.41	15.75	79.70	18.18	21.11	13.31
	(32.59)	(5.42)	(11.27)	(5.08)	(12.25)	(4.96)
Winter Legume Cover Crop (WLCC)	29.92	5.46	48.21	6.37	11.64	4.55
	(21.67)	(3.38)	(8.45)	(4.26)	(12.61)	(2.23)

Note: Values in parentheses are standard errors.

opportunity cost of abating one pint of herbicides, once all inefficiency is taken into account, is just under $40, while the opportunity cost of foregoing one trip across the field is just under $10. Alternatively, a producer operating at a zero herbicide level could increase output by approximately $37 if an additional pint of herbicide was applied. Prices for each proxy are generally higher for corn ($59 and $10) than for tomatoes ($16 and $7), and the organic system tends to admit shadow prices higher than the overall average. Standard tillage shadow prices are lower than average for herbicides, but higher than average for number of trips across a field.

Overall shadow prices for abatement of herbicides and trips are generally higher than the comparable input costs for herbicides and labor, which range between $3 and $20 per pint for herbicides, and $1.75 to $4 for the 0.13 to 0.30 hours of machine labor used per trip. This evidence of a lack of allocative efficiency is likely explained by the nature of the data, as the behavioral assumption of profit maximization is not maintained in the agronomic experiments. One advantage of the methodology, however, is that it allows for calculation of shadow prices in the *absence* of that assumption, using data generated through plot-level field trials. Furthermore, the estimates illustrate that use of prices of inputs correlated with pollution may underestimate the costs of abatement in the presence of allocative inefficiencies.

From a policy perspective, estimation of shadow values at the plot level across production systems can serve several purposes. First, in the presence of existing or potential environmental legislation, these prices can inform individual growers as to the opportunity costs of either reducing polluting inputs or switching production systems, thus potentially resulting in a more optimal mix of production technologies from the social perspective. Second, this application highlights the potential heterogeneity of abatement costs across crops and production systems, suggesting the need for targeted, rather than blanket, environmental policy. Finally, these prices can be used as theoretically consistent prices in relevant environmental/sustainability indices and benefit/cost analyses to guide public policy with respect to optimal environmental policy as it applies to agricultural issues.

Conclusions

This paper has estimated the production technology used to produce corn and processing tomatoes at an experimental plot level using data from the Sustainable Agriculture Farming Systems study at the University of California, Davis. In addition to simple measures of technical efficiency generated by the ratio of multilateral desirable output to input index ratios, a directional output distance function was estimated in order to incorporate proxies for environmental pollution as nondesirable inputs, and the resultant efficiency rankings were analyzed. This approach allows for simultaneous crediting of increases in desirable output and decreases in undesirable outputs in the efficiency calculations, thereby allowing for a univariate measure of a multivariate concept and facilitating comparisons between production systems along both environmental and economic dimensions. Additionally, as the directional distance function is a complete representation of the technology, the marginal rate of transformation between "goods" and "bads" along the frontier can be utilized to estimate the shadow price of pollution abatement, so long as one assumes that at least one market price equals the corresponding shadow price.

Results showed that conventional production technologies were most efficient when environmental considerations were not taken into account for both corn and tomatoes, and that an organic system ranked last for this criterion for each of the crops. Once the environmental proxies were included, however, organic systems increased in efficiency relative to the other systems, while the winter legume cover crop systems were deemed less efficient. Average shadow price estimates for pints of herbicides ranged from \$23–\$37, while shadow prices for trips across the field averaged \$8–\$21. Like similar studies, there was considerable variation in shadow prices between observations.

The major conclusions to be drawn from this study are: (*a*) productivity rankings by production system are sensitive to the inclusion of undesirable outputs; and (*b*) in the agricultural production setting, there are tradeoffs between environmentally-friendly farming practices that reduce externalities and desirable output, and these tradeoffs can be quantified in terms of shadow prices. These shadow prices can be used in cost-benefit analyses and other economic analyses in order to inform policy makers and other interested parties about the tradeoffs involved in pollution abatement.

While this paper contributes to the understanding of these tradeoffs, future research is needed to both verify and extend these findings. Ideally, actual environmental pollution data could be used in place of the proxies used here, or barring that, data generated from an agronomic simulation model. In addition, due to data limitations, the analysis presented here treats the observations as a cross-section, rather than a true panel with a time dimension. Future research could exploit this additional dimension to examine trends in both efficiency measurements and shadow prices, especially as environmental regulations tighten for the agricultural sector. Finally, further research is necessary to compare and contrast these results across sites, years, crops, and production technologies.

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