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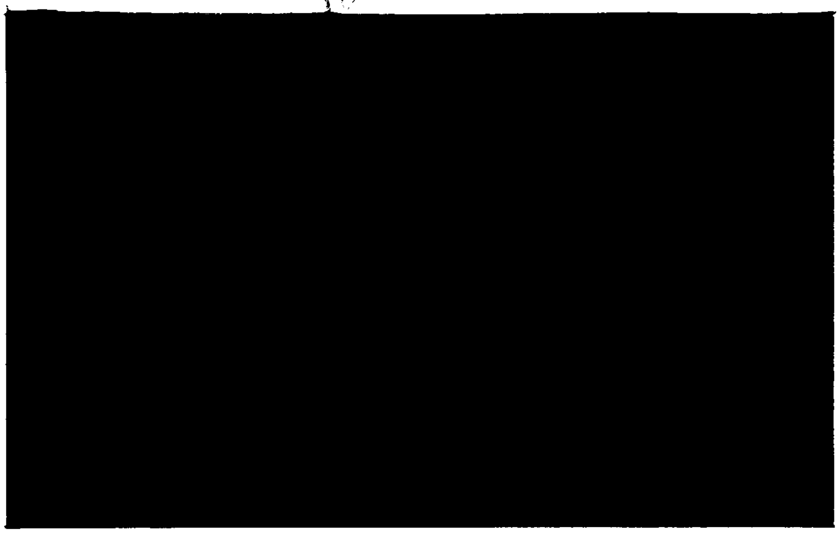

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Simple Econometrics of Pesticide Productivity

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Simple Econometrics of Pesticide Productivity

Introduction

Productivity is central to policy debates about pesticides. The answers to questions such as whether restrictions on pesticide use are warranted, whether taxes should be used instead of current direct regulations, how reduction or elimination of pesticide use would affect national income, soil erosion, and other aspects of environmental quality—all hinge on the role pesticides play in production.

Economists have made only limited contributions to the discussion of these issues. The few studies that estimate the effects of broad-scale usage restrictions on national income (Knutson et al.; Zilberman et al.; Osteen and Kuchler) have relied on crop scientists' estimates of average productivity effects on different crops. Econometric evidence about pesticide productivity, substitution possibilities between pesticides and other inputs, and the determinants of pesticide demand has been limited to a handful of crops in a few production regions (see for example Carlson; Campbell; Lee and Langham; Pingali and Carlson; Babcock, Lichtenberg and Zilberman. Headley, Clark and Carlson, and Carrasco-Tauber and Moffitt provide aggregate analyses) and has not been used for policy analysis. Instead, economic analyses have relied on crop scientists' assessments of pesticide productivity, which are formulated in terms of averages in a few discrete technological packages rather than in more economically relevant marginal terms. Lacking the flexibility and the stress on substitution relationships characteristic of an economic production model, these assessments are likely to miss important information about actual production practices as they occur in practical circumstances when farmers simultaneously make both economic and technical decisions. Thus, sound empirical methods for estimating pesticide productivity from actual (versus experimental) data are sorely needed.

Lichtenberg and Zilberman (LZ) have proposed a framework for econometric estimation of pesticide production functions based on a recognition of the particular role pesticides play as damage-control agents. Advantages of this framework include separate representations of the damage control and pure productivity effects of inputs used for multiple purposes (e.g., cultivation or pruning) and implicit estimation of pest damage that can be used to validate the assessments of crop scientists. LZ also argue that more traditional specifications produce overestimates of pesticide productivity. Babcock, Lichtenberg and Zilberman applied the LZ damage control framework to North Carolina apple production using an exponential representation of damage. Carrasco-Tauber and Moffitt compared a Cobb-Douglas production function with exponential, logistic, and Weibull damage specifications in estimating pesticide productivity in aggregate U.S. crop production.

This paper develops a dual representation of damage control technology and illustrates its use in estimating pesticide productivity using aggregate U.S. data. Our first contribution is to develop a multioutput generalization of the original LZ contribution. The dual version of the generalized LZ model is then shown to be conditionally additive in the prices of abatement activities and other prices. An econometric procedure for estimating the dual technology is then developed and illustrated by applying it to an aggregate U.S. agricultural data set.

The Dual Structure of Pesticide Technologies

The theoretical development is for a multiple-output technology represented by a production possibilities set $T \subseteq \mathbf{R}^{m+n}_{+} \times \mathcal{P}$ where $\mathcal{P} = [0,1]$:

$$T = \{(x,g,y): (x,g) \text{ can produce } y\}.$$

Here $x \in \mathbf{R}^n_+$ is a vector of inputs, $g \in \mathcal{P}$ is a single input which we shall refer to as abatement, and $y \in \mathbf{R}^m_+$ is a vector of outputs. T is a nonempty, closed, convex set that satisfies free disposability of both inputs and outputs (Chambers, Chapter 7).

Abatement is an intermediate or aggregate input produced by combining different forms of pesticides and other preventive inputs. This intermediate production process is represented by the nondecreasing, concave function $G: \mathbf{R}^m_+ \to \mathcal{P}$,

$$g = G(z),$$

where $z \in \mathbf{R}^s_+$ is a vector of inputs that affect only abatement. As LZ note, abatement cannot exceed potential output (output in the absence of damage). Thus, abatement can be scaled to lie between 0 (no abatement) and 1 (perfect abatement and thus no damage), hence, the choice of the domain for G.

The first step in representing the dual pesticide technology is to characterize the cost of abatement function $c: \mathbf{R}^s_+ \times \mathcal{P} \to \mathbf{R}_+$ defined by

$$c(v,g) = \text{Min}_z \{vz: G(z) \geq g\},$$

where $v \in \mathbf{R}^s_+$ is a vector of preventive-input prices. Apart from the restricted domain of g, c(v,g) is a standard single-output cost function with the following properties: positive linear homogeneity and concavity in v, nondecreasing in v, nondecreasing and convex in g. Moreover, it satisfies Shephard's lemma: If a unique solution exists to this minimization problem it can be recaptured by differentiating c(v,g) with respect to v. Hence, the derived demands for a given abatement level are

$$z(v,g) = c_v(v,g),$$

where the subscript denotes the gradient of the subscripted function.

Assuming that farmers are profit maximizers, the profit function is defined by

$$\pi(p,w,v) = \text{Max}_{y,x,z} \{py - wx - vz: (x,G(z),y) \in T\}.$$

Here $p \in \mathbf{R}^m_{++}$ is a vector of output prices and $w \in \mathbf{R}^n_{++}$ is a vector of input prices for $x \in \mathbf{R}^n_+$. $\pi(p,w,v)$ is positively linearly homogenous and convex in all prices, nondecreasing in p, and nonincreasing in w and v. If a unique solution to the optimization problem exists it can be recaptured by differentiation of the profit function via the Hotelling-Shephard lemma.

The specialized nature of T allows further inferences about the structure of $\pi(p,w,v)$ that prove econometrically useful in modelling the production technology. Notice that

$$\begin{aligned}
(1) \qquad \pi(p,w,v) &= \text{Max}_{y,x,z} \{py - wx - vz: (x,G(z),y) \in T\} \\
&= \text{Max}_{y,x,g} \{py - wx - \text{Min}_z \{vz: G(z) \geq g\}: (x,g,y) \in T\} \\
&= \text{Max}_{y,x,g} \{py - wx - c(v,g): (x,g,y) \in T\} \\
&= \text{Max}_g \{\text{Max}_{y,x} \{py - wx:(x,g,y) \in T\} - c(v,g)\} \\
&= \text{Max}_g \{R(p,w;g) - c(v,g)\}.
\end{aligned}$$

$R(p,w;g)$ is a restricted (short-run) profit function defined for a given abatement level. It represents the maximum restricted profit, i.e., exclusive of pesticide costs, given abatement. Its properties include: positive linear homogeneity and convexity in prices, nondecreasing in p, nonincreasing in w, and nondecreasing and concave in g (Chambers, Chapter 7). $R(p,w;g)$ also satisfies the Hotelling-Shephard lemma, so that if it is differentiable its restricted-profit maximizing supply vector for a given abatement level is

$$y(p,w;g) = R_p(p,w;g)$$

while its restricted-profit maximizing derived demands are

$$x(p,w;g) = -R_w(p,w;g).$$

Several comments should be made about $R(p,w;g)$. First, the maximum restricted profit available for prices (p,w) is $R(p,w;1)$. Second, the minimum restricted profit available for prices

(p,w) is R(p,w;0). This follows because R(p,w;g) is nondecreasing in g. One might naturally suppose that the maximum amount of the i^{th} output that a profit maximizing farmer would produce for prices (p,w) is given by $\partial R(p,w;1)/\partial p_i$. This may not be true because there is no reason, *a priori*, for all outputs to be nondecreasing in abatement. For the scalar output case, however, $R_p(p,w;1)$ represents the maximum output a restricted profit maximizing firm will produce and $R_p(p,w;0)$ represents the minimum. Finally, the derivative $R_g(p,w;g)$ is the shadow value of abatement activities to the farmer.

$\pi(p,w,v)$ is *conditionally additive* in (p,w) and v, that is, the optimization problem can always be viewed as solving the first-order condition for the last equality in (1):

$$R_g(p,w;g) = c_g(v,g). \tag{2}$$

Abatement is chosen to equate its marginal return to its marginal cost. The curvature properties of R(p,w;g) and c(v,g) guarantee that any solution to (2) is a global solution to (1).[1] In what follows denote the solution to (2) as g(p,w,v).

The terminology 'conditionally additive' means that given g, the profit function has (p,w) additively separable from v and vice versa. To see the economic consequences of conditional additivity, apply the Hotelling-Shephard lemma and use the envelope theorem with (1) to get the following expressions for the profit-maximizing supply vector, the profit maximizing x vector, and the profit maximizing z vector, respectively:

$$y(p,w,v) = \pi_p(p,w,v) = R_p(p,w;g(p,w,v))$$

$$x(p,w,v) = -\pi_w(p,w,v) = -R_w(p,w;g(p,w,v))$$

$$z(p,w,v) = -\pi_v(p,w,v) = c_v(v, g(p,w,v)).$$

The conditionally additive structure of the pesticide technology insures that the effects of perturbations in v manifest themselves on y and x only through adjustments in abatement.

Similarly, changes in p and w only manifest themselves on z in the form of induced adjustments to changes in abatement.

An Econometric Approach for Estimating the Technology

LZ's main criticism of previous econometric approaches is that they ignored the biological role that pesticides play in agricultural production technologies. This results in a loss of econometric efficiency and presumably in frequently implausible estimated agricultural technologies. In a dual context, a similar mistake is made by pursuing a standard approach to estimation, i.e., specifying a flexible form for $\pi(p,w,v)$ and then using the following version of the Hotelling-Shephard Lemma as a basis for estimation:

$$y(p,w,v) = \pi_p(p,w,v)$$

$$x(p,w,v) = -\pi_w(p,w,v)$$

$$z(p,w,v) = -\pi_v(p,w,v).$$

Suppose that a generalized-Leontief profit function were specified and that these equations were converted to stochastic form to be used as the basis for estimating the parameters of the generalized-Leontief profit function. One might achieve statistically plausible estimates, but such a system does not capture the full richness of the unique role that abatement activity plays in the LZ biological production model and thus can result in implausible results. For example, in this formulation it is not uncommon to encounter empirically estimated pesticide demand equations which are positively sloped (Chambers and Pope).

$R(p,w;g)$ and $c(v,g)$ are sources of information on the technology, so using them in estimation should increase estimation efficiency. Once characterized econometrically, $R(p,w,g)$, $c(v,g)$, and (1) can be used to generate $\pi(p,w,v)$.

Our econometric approach rests on specifying suitably flexible versions of R(p,w;g) and c(v,g), and then basing estimation on the following version of the Hotelling-Shephard Lemma:

(3) $$y(p,w,v) = R_p(p,w;g(p,w,v))$$
$$x(p,w,v) = -R_w(p,w;g(p,w,v))$$
$$z(p,w,v) = c_v(v, g(p,w,v)).$$

Given observations on y(p,w,v), x(p,w,v), z(p,w,v), and g(p,w,v), equations (3) can support estimation of the parameters of R(p,w;g) and c(v,g). Unfortunately, observations on damage or abatement are rarely available. Typically, therefore, one must specify a parametric representation of G, and then substitute G(z(p,w,v)) into the right-hand side of (3) to get:

(3′) $$y(p,w,v) = R_p(p,w; G(z(p,w,v)))$$
$$x(p,w,v) = -R_w(p,w;G(z(p,w,v)))$$
$$z(p,w,v) = c_v(v, G(z(p,w,v))).$$

After specifying a suitable error structure, (3′) can be used to estimate the parameters of R(p,w;g), c(v,g), and G(z).

Several problems must be addressed. Expressions (3′) have z(p,w,v) on both sides of the equalities. z(p,w,v) represents a vector of choice variables and hence must be treated as endogenous for econometric purposes. Thus, simple multivariate regression techniques cannot be applied to (3′). Second, because c(v,g) and G(z) are dual relations, they contain the same information, so the last set of equations in (3′) can be redundant. This can be seen by considering the case of scalar z, where the last equation in (3′) degenerates to an identity which adds no information in econometric estimation. (For a single-input, abatement function $c_v(v,g)$ is the reciprocal image of G(z).)

A consistent approach is to develop an instrumental regression of observed z on p,w, and v from the relationship,

$$z(p,w,v) = c_v(v,g(p,w,v)).$$

Because g(p,w,v) depends upon the parameters of R(p,w;g), the parameters of either c(v,g) or R(p,w;g) usually cannot be identified from this regression, but a consistent estimate of z(p,w,v) is available. An obvious choice is to approximate this reduced form with a suitably flexible functional form. Once this regression has been fit, then predicted values for the z(p,w,v) can be fit and inserted into the first m+n equations in (3′) which can then be used to estimate the parameters of R(p,w;g) and G(z) jointly. The cost correspondence can then be used to generate c(v,g).

Another approach relies on recognizing that g(p,w,v) solves

$$R_g(p,w;g(p,w,v)) = c_g(v,g(p,w,v)), \tag{4}$$

which is the first-order condition for (1). If a closed form solution to (4) exists, it can substitute into the right-hand side of (3). Two things should be noted about this approach. First, g(p,w,v) will depend upon the parameters of both R(p,w;g) and c(v,g). Thus, even if these functions are linear in parameters, nonlinear regression techniques will be necessary. Second, because this approach uses all available information it should be efficient econometrically *for given* R(p,w;g) and c(v,g). An important drawback, however, is computational complexity.

A third alternative, which we pursue and is fully explained below, is to use the solution to (4) in an instrumental-variable regression to estimate only the parameters of c(v,g). Once this is done, an estimate of G(z) can be created and used in (3).

Before leaving this section it is worthwhile to consider the standard approach for dealing with intermediate and aggregate inputs (e.g. Ball (1988)). Empirically, separable structures are usually used to justify the creation of aggregate inputs and aggregate input prices. This approach also presumes the input aggregators are homothetic. Suppose that G(z) is homothetic. Then the abatement cost function must assume the general form h(g)c(v) (Chambers, Chapter 2), where c(v) is a cost function for a linearly homogeneous technology. Hence,

$$\begin{aligned}\pi(p,w,v) &= \text{Max}_g\{R(p,w;g) - c(v,g)\} \\ &= \text{Max}_g\{R(p,w;g) - c(v)h(g)\} \\ &= \pi^*(p,w,c(v)),\end{aligned}$$

where $\pi^*(p,w,c(v))$ satisfies all the properties of profit functions in p,w, and c(v). Thus, c(v) can be treated exactly as if it were an input price. Unfortunately, our *a priori* knowledge of G(z) implies that it cannot be homothetic, so this construct is not available here.

An Empirical Specification

To illustrate the procedures discussed above, we use an aggregate, time-series (1949-1990) data set for the United States agricultural production sector that has been the basis for a number of other empirical studies of supply-response in U.S. agriculture (Ball (1985); Ball (1988); Chavas and Cox; Chambers and Pope) using a variety of empirical techniques. These data were graciously supplied by V. Eldon Ball of the Economic Research and are described in detail in Ball (1985) and Ball (1988). Aggregate U.S. agricultural production (Y) is presumed to depend upon six aggregate inputs: land (A), labor (L), pesticides (Z), fertilizer (F), materials (M), and capital (K). The aggregate technology is described by a concave production function in which abatement activity enters multiplicatively as in Babcock, Lichtenberg and Zilberman and Carrasco-Tauber and Moffitt:

$$Y = G(Z)H(L, F, M, K, A; t).$$

Here t stands for time and indexes the state of the technology at time t. It is included because our data are time series in nature. This specification requires production to be zero when abatement is zero. When abatement equals one, maximum agricultural output is given by H(L, F, M, K, A, t). However, abatement is not necessarily zero when Z is zero, i.e., G can be specified so that $G(0) > 0$. In this case, G(0)H(L, F, M, K, A, t) gives output in the absence of pesticides.

Our main assumption here is that the abatement model applies at the aggregate level. We do not presume that the production structure specified above and estimated below emerges from the consistent aggregation of microeconomic entities to the macro level. Indeed, this presumption is untenable in the context of the abatement model specified above. To see why consider the following thought experiment: Suppose that there are N firms each of which uses the same amount of L, F, M, K, and A but different amounts of pesticides. Using a subscript i to denote the i^{th} firm, the i^{th} firm's output is then:

$$Y_i = G(Z_i)H(L, F, M, K, A; t)$$

and total output is

$$Y = \sum_i Y_i = \sum_i G(Z_i)H(L, F, M, K, A; t).$$

To be able to construct a model of aggregate output one must have observations on each firm's use of pesticides. Our data is for aggregate pesticide utilization. Thus, if our above specification were to result from consistent aggregation of these microeconomic entities it must be true that

$$G(Z) = \sum_i G(Z_i),$$

where we remind the reader that Z now stands for aggregate pesticide usage, $\sum_i Z_i$. This last equation is known as Cauchy's equation and it is well known (Aczel) that it can only apply if

G(z) is linear, i.e., G(z) = gz. But as pointed out above, linearity of G(z) violates the basic abatement properties because a linear function cannot be constrained to lie in the unit interval.

Another problem with assuming that the aggregate production structure results from the consistent aggregation of profit maximizing entities is the impossibility result reported in Pope and Chambers which demonstrates that one cannot create quantity aggregates for profit maximizers which are the sum of micro quantities and still satisfy the homogeneity properties for each of the individual profit maximizers. Because we intend to estimate a restricted-profit function, the Pope-Chambers impossibility result applies. Thus, we follow standard practice in the aggregate empirical production literature (Antle, Ball (1986), Lee and Chambers, Ball (1988), Capalbo and Denny, Chavas and Cox) and assume that the theory deduced for microeconomic entities applies at the aggregate level. This assumption has well-known limitations and the usual caveats apply here. However, this assumption also has served as the basis of much of the existing empirical literature in applied production and consumption analysis. In fact, much of our empirical knowledge of supply-response systems, the conventional wisdom so to speak, is based upon models which fail the Pope-Chambers impossibility criterion.

Besides the aggregation-across-firms problem, there also exists the problem of using a single scalar measure of pesticide applications. Our theory has been derived for the case where z is a vector. Our empirical application utilizes a single implicit Tornqvist quantity index of all pesticides (see Ball (1985) for a discussion of its derivation). Other aggregate analyses of pesticides use different measures of aggregate pesticide use. Clark and Carlson used total pounds of insecticides, fungicides and herbicides, which has the advantage of separating types of pesticides, but does so only to a limited extent and which has the disadvantage of aggregating chemicals of differing effectiveness. Carrasco-Tauber and Moffitt, following Headley, used

average per-farm expenditures on all pesticides, a measure that confounds price and quantity effects and, hence, cannot be strictly interpreted as an input. Moreover, more effective pesticides both are used in smaller quantities and tend to be more expensive, so it is unclear whether expenditures capture variations in quality. Our measure is thus preferable to using expenditures or sums of raw quantities on conceptual grounds. However, use of any single measure of pesticide use inevitably implies the loss of precision and reality in estimation and thus must dictate caution in the interpretation of our results.

The problem of aggregation is not unique to pesticides, but applies to all indexes and aggregates of both input and output quantities derived by combining disparate inputs and output. Thus virtually all applied production models, even many cross-sectional ones, suffer from this problem. This shortcoming may be less apparent in traditional production analyses because they do not focus on the roles that specific inputs play in the production process, but it is none the less real.

These considerations suggest that the development of aggregate data sets and notions of aggregation which circumvent these difficulties is an important area for future research. They also suggest that our dual representation of the LZ specification can be only be fully accepted after it has been thoroughly tested using appropriately aggregated data sets and cross-sectional data sets. Both of these are major research tasks in their own right and go far beyond the scope of the present paper which is to develop a generalization of the LZ representation, develop the dual implications of the generalization, and present an empirical illustration of how to apply the new methodology implied by the latter developments. Our future research will address both the aggregation issue and consider cross-sectional tests of the generalized model presented in the first section.

Because our data are predicated upon the assumption of constant returns to scale (Ball (1988)), we impose constant returns in all inputs but time. Hence,

$$Y' = G(Z/A)H(L/A, F/A, M/A, K/A, 1; t) = G(Z')h(L', F', M', K'; t)$$

where primes (′) denote per-acre amounts.

We consider two representations of abatement, an exponential and a logistic, both of which have closed-form solutions for pesticide demand.[2] The exponential specification is:

$$G(Z') = 1 - \exp(\alpha - \lambda Z')$$

where α and λ are parameters. If $\lambda > 0$, this abatement function is both nondecreasing and concave as required. Dual to this abatement function is

$$c(v,g) = v[\alpha - \ln (1-g)]/ \lambda,$$

which satisfies all the standard properties of cost functions. The logistic specification is:

$$G(Z') = 1/[1 + \exp(\theta - \psi Z')]$$

where θ and ψ are parameters. Dual to this abatement function is

$$c(v,g) = v[\theta - \ln((1-g)/g)]/\psi,$$

which satisfies the standard properties of cost functions for $g > ½$.

Dual to the production function is the restricted profit function (land held fixed):

$$R^*(p,w; A, g, t) = \mathrm{Max}_{L,F,W,K}\{pgH(L, F, M, K, A;t) - w_L L - w_F F - w_m M - w_K K\}$$

$$= \mathrm{Max}_{L',F',M',K'} A\{pgh(L', F', M',K';t) - w_L L' - w_m M' - w_F F' - w_K K'\}$$

$$= A\, R^{\circ}(p^*, w_L, w_F, w_m, w_K;t)$$

where $p^* = pg$, and

$$R^{\circ}(p^*, w_L, w_F, w_m, w_K; t) = \mathrm{Max}\ \{p^*h(L', F', M',K';t) - w_L L' - w_m M' - w_F F' - w_K K'\}$$

is a restricted profit function and is appropriately interpreted as the marginal (average) land rent. $R^{\circ}(p^*, w_L, w_F, w_m, w_K; t)$ is the focus of the rest of the analysis. The presumption that abatement shifts production multiplicatively has the dual reflection that abatement can be modelled as if it multiplicatively rescales the output price. Structurally, this is similar to the way in which output augmenting technical change is modelled. Econometrically it has several very interesting implications: Once $R^{\circ}(p^*, w_L, w_F, w_m, w_K; t)$ is estimated, the maximum restricted profit per acre is $R^{\circ}(p, w_L, w_F, w_m, w_K; t)$. Maximum output consistent with restricted profit maximization is $R^{\circ}_l(p, w_L, w_F, w_m, w_K; t)$ by the Hotelling-Shephard Lemma, and per-acre input utilization consistent with maximum abatement is $-R^{\circ}_w(p, w_L, w_F, w_m, w_K; A)$.

Our econometric approach uses expression (4) and the Hotelling-Shephard Lemma to solve for the optimal level of abatement:

$$g = \lambda pY'/ (\lambda pY' + v)$$

for the exponential abatement technology and

$$g = (\psi pY' - v)/\psi pY'$$

for the logistic abatement technology. Using these results in the last equation in (3) gives the optimal level of pesticide use

$$Z' = \lambda^{-1} [\alpha + \ln(\lambda pY' + v) - \ln v] \quad \text{(5a)}$$

in the exponential case and

$$Z' = \psi^{-1}[\theta + \ln(\psi pY' - v) - \ln v] \quad \text{(5b)}$$

in the logistic case.

The parametric specification of $R^{\circ}(p^*, w_L, w_F, w_m, w_K; t)$ is the modified generalized-Leontief form

$$R^{\circ}(p^*, w_L, w_F, w_m, w_K; t) = (a_p p^* + \sum_i b_{pi}(w_i p^*)^{1/2} + 1/2 \sum_i \sum_k b_{ik}(w_i w_k)^{1/2})$$

$$+ t(\tau_p p^* + \sum_i \tau_i w_i),$$

where a_p, b_{ik}, and the τ_i are parameters to be estimated, and $b_{ik} = b_{ki}$. Apply the Hotelling-Shephard lemma to get the following expressions for the aggregate per-acre supply and derived demands for a given g:

$$(6) \qquad Y' = [(a_p + 1/2\sum_i b_{pi}(w_i / p^*)^{1/2}) + t\tau_p]g,$$

$$I = [b_{pI}(p^*/w_I)^{1/2} + \sum_i b_{Ii}(w_i / w_I)^{1/2}] + \tau_I w_I \qquad (I = F', L', K', M').$$

Together expressions (5) and (6) describe the aggregate supply-response system including the specified pesticide demand equation. To each equation in (5a,b) and (6), we appended an additive error term. Assume that each of these error terms is independently, identically distributed over time around a mean of zero and contemporaneously correlated with one another.

The system of equations represented by (5a or 5b) and (6) is a nonlinear, simultaneous equations system. Consistent estimates were obtained using the following three-stage strategy. In the first stage, a reduced-form equation for pY′ was estimated using a flexible functional form of all the prices in the system and time. That estimated equation was used to create a predicted value for pY′. In the second stage, expression (5) was estimated by nonlinear least squares after replacing pY′ with its predicted value. This yields a consistent estimate of α (θ) and λ (ψ) in the exponential (logistic) case. When combined with the fitted value of pesticide demand obtained from the estimated version of (5), these estimates provide a consistent estimate of g(p,w,v). This predicted value for g was then substituted into (6) which was estimated using Zellner's seemingly unrelated regression technique using SAS/PC. At the suggestion of a reviewer two versions of both models were fit: one version that corrected for potential autocorrelation problems in the estimated residuals and one that did not. We corrected for autocorrelation for both the pesticide demand equation and the restricted profit system. To correct for potential autocorrelation problems in the pesticide demand equation, we took the estimated residuals from the uncorrected model and used these to perform a Cochrane-Orcutt correction of the data and then refit the corrected model using nonlinear least squares. For the restricted profit system, Parks' generalization of Zellner's seemingly unrelated regression technique was applied to the system of equations described above. This estimation was done in LIMDEP. With one exception discussed below, the qualitative results for both versions of the model were highly similar. All estimation was performed on a Gateway 2000 486DX/33 computer.[3]

Empirical Results

Table 1 report two sets of estimated parameters and their standard errors corresponding to the exponential and logistic abatement models. Both models give virtually identical results, suggesting that the estimates are robust with respect to small changes in the specification of G(z). To conserve space we only report estimates from the uncorrected system. Estimates from the autocorrelation-corrected model are available upon request from the authors.

Estimated Damage

The estimated parameters can be used to construct consistent estimates of abatement, G(z), and percentage pesticide damage, 1 - G(z), using the fitted values of pesticide demand, Z'.[4] Because we use a single-product specification, our abatement estimates are for total U.S. agricultural output, including both crops and animal products. Depending on the year, animal products represent between 47 and 60 percent of the total, with this share falling over time. If we adopt the plausible assumption that pest damage to animal products is negligible, i.e., that all

pesticide use is directed toward crops, then, letting σ be the share of crops in the value of total output, crop damage can be estimated as

$$1 - G(Z') = \exp(\alpha - \lambda Z')/\sigma$$

in the exponential case and

$$1 - G(Z') = \exp(\theta - \psi Z')/(\sigma[1 + \exp(\theta - \psi Z')])$$

in the logistic case.

Using this admittedly crude approximation, both models indicate crop damage on the order of 15 percent during the early 1950's and crop damage falling steadily as pesticide use spread, reaching 11 percent in the mid 1960's, 6 percent in the mid 1970's and stabilizing at about 3 percent from 1979 through the ensuing decade. (The autocorrelation-corrected model suggested slightly higher crop damage in the early 1950s, approximately 20 percent, but virtually identical estimates of crop damage for the rest of the sample period.) Thus, our results suggest much lower losses from pest damage than estimated by crop scientists (see for example Cramer and Pimentel et al.). One explanation is that their studies may ignore the full range of adjustments that farmers make in actual field conditions. However, the highly aggregate nature of our data, discussed above, dictates a need for caution in the interpretation of our results and for further research applying our methods to more disaggregate data to draw firm conclusions on actual damage levels.

In interpreting our damage estimates, one should also recognize that much more precise estimates of crop damage can be achieved by using the multioutput production model developed in the theoretical section. We did not pursue that approach here because our data were limited and our primary focus in this study is on developing a workable and flexible alternative to current pesticide modelling practices, which are all single product in nature.

Estimated Supply and Demand Elasticities

For the supply-response system, two sets of elasticities are relevant. The first are the short-run elasticities corresponding to fixed abatement levels. These elasticities can be calculated from the estimated parameters, e.g., the supply elasticity is calculated as $pgR^{\circ}_{11}(pg,w)/R^{\circ}_{1}(pg,w)$. These elasticities are reported, at sample means, for both versions of the model in Table 2a. No short-run pesticide elasticity is reported because for a fixed g pesticide demand is perfectly price-inelastic in our specification. All elasticities are of the expected signs in both versions of the model and compare favorably with other elasticities estimated from aggregate data (Antle; Ball (1988)). Although all elasticities are of the expected signs, the estimated $R^{\circ}(pg,w)$ is not convex at all data points. In particular, at the sample mean one of the calculated eigenvalues for the Hessian matrix of $R^{\circ}(pg,w)$ in prices is slightly negative. Therefore, we cannot conclude that the estimated $R^{\circ}(pg,w)$ is convex at that point. Nonconvexity of $R^{\circ}(pg,w)$, however, is not a problem unique to this study, and similar problems have been encountered with other versions of this data set (Ball (1988)). The typical method for resolving this problem is to impose convexity upon the data using either the methods of Lau or Diewert and Wales. We did not pursue this option, which involves substantial additional computational complexity, because of the limited aims of the present study, i.e., illustrating an estimation procedure.

The second set of elasticities reported are the long-run elasticities that exploit the conditionally additive nature of the LZ model. These elasticities correspond to the optimal solution to (1). Thus, they characterize implicitly $\pi(p,w,v)$, and, in principle, could be integrated to obtain $\pi(p,w,v)$. Our strategy for calculating them exploits expression (2) and the fact that, e.g.,

$$y_v(p,w,v) = \pi_{pv}(p,w,v) = R_{pg}(p,w;g(p,w,v))g_v(p,w,v)$$

where $g_v(p,w,v)$ is calculated by implicit differentiation of (2). These long-run elasticities are reported in Table 2b. Again the estimates for both specifications of abatement are virtually identical. The short-run and long-run elasticities are subject to the LeChatelier Principle, i.e., long-run, own-price elasticities exceed the corresponding short-run elasticities in absolute value. Our calculations numerically confirm this principle. All elasticities are of the expected sign and of plausible values when compared with other studies (see for example Antle; Ball (1988)).

Negative cross-price elasticities indicate that labor, fertilizer, materials and capital are all complementary with pesticides. (For the autocorrelation-corrected model pesticides and fertilizer are substitutes.) Because these cross-elasticities are all small (the largest is under 0.11), reductions in pesticide use, *ceteris paribus*, will likely occasion at most rather modest decreases in these inputs; this is in accord with a growing conventional wisdom.

The elasticity of pesticide demand with respect to output price is quite high, roughly 2.7 in both specifications. This empirical result, which is affirmed by the autocorrelation-corrected version of the model, supports the increasingly widely held belief that pesticide use would be substantially lower in the absence of farm subsidies (see for example Reichelderfer).

Elasticities of abatement derived from the pesticide-elasticity estimates are reported in the last line of Table 2b. Abatement is extremely inelastic to changes in all input prices implying that even relatively large changes in price will have small effects on abatement levels and thus pest damage. This result, too, is in accord with LZ's prediction about the behavior of abatement as it approaches 1 and with the results from the autocorrelation-corrected model.

For purposes of comparison, the long-run elasticity estimates for the autocorrelation-corrected system are reported in Table 2c. We found somewhat lower price responsiveness for the restricted profit system estimated using Parks' procedure than for the system not corrected for

autocorrelation. For example, pesticide demand is own-price inelastic in the corrected system but elastic in the uncorrected system. All own-price elasticities in the autocorrelation-corrected system are of the expected sign, but all are also somewhat lower than those reported above. The elasticity estimates from both systems are well within the range of other estimates presented in the literature. The main qualitative difference between the results reported in Table 2b and those reported in Table 2c are that fertilizer emerges as a regressive input (its utilization rises as the price of output falls) in the autocorrelation-corrected version of the model.

Maximum Output, Minimum Output, and Actual Output

Maximum potential output, $R_p(p,w,1)$ gives an upper bound on crop profit maximizing production. Damage in the absence of pesticides G(0) gives an upper bound on damage, so that output in the absence of pesticides, $R_p(p,w,G(0))$, gives a lower bound on profit maximizing aggregate production. Figures 1 and 2 compare pictorially, for the sample period, our estimates of aggregate production under actual pesticide use with estimated maximum potential output, $R_p(p,w,1)$ and with output at actual prices and zero pesticide use, $R_p(p,w,G(0))$, for the exponential and logistic specifications, respectively. (The autocorrelation-corrected system yields virtually identical versions of Figures 1 and 2.) Prior to the widespread adoption of pesticides, damage was close to the lower bound. As pesticide use increased, output moved closer to the upper bound of maximum potential output, stabilizing at close to 99 percent of it.

Damage Control vs. Conventional Specifications

One of the key elements of the LZ critique of traditional production modelling is that by ignoring the biological content of agricultural production relations, it can unknowingly introduce biases into empirical estimates of the technology. Therefore, to assess the difference that our approach makes in modelling, we have estimated an alternative model that ignores the unique role that abatement activities play in agricultural production models. The most natural alternative to our model is a generalized-Leontief specification of $\pi(p^*,w,v,t)$ (i.e., a generalized-Leontief, land-rent function)

$$\pi(p^*,w,v,t) = (a_p p^* + a_v v + \sum_k b_{kv}(w_k v)^{1/2} + b_{vp}(vp)^{1/2} + \sum_i b_{pi}(w_i\ p^*)^{1/2} + 1/2\ \sum_i\sum_k b_{ik}(w_i\ w_k)^{1/2}) + t(\tau_p p^* + \sum_i \tau_i w_i + \tau_v v),$$

(The parameters of $\pi(p^*,w,v,t)$ are not the same as the parameters of R°.) This specification was estimated using the same empirical procedures as to estimate the parameters of R°. The estimated parameters are reported in Table 3 and elasticities evaluated at the sample mean are reported in Table 4. (Only one set of elasticities are reported because this profit function is not conditionally additive.) Although a perusal of the estimated parameters suggests this model fits the data rather well, a glance at the elasticity matrix reveals a problem. At the mean of the data (and at other data points), the pesticide demand equation is upward sloping, suggesting that raising the price of pesticides actually increases pesticide usage. Other occurrences of estimated pesticide demand equations sloping in the wrong direction are not unknown in the empirical production literature (Chambers and Pope). Various heuristic explanations for this phenomenon have been offered. But the success of our model in capturing the appropriate slope of the pesticide demand equation suggests that the problem may lie in specifications that ignore the restrictions arising from the nature of damage control.

Besides the presence of an upward sloping pesticide demand problem, this production model encountered severe problems with satisfying the convexity properties of profit functions. At the sample mean, three of the eigenvalues calculated for the Hessian matrix of the profit function were negative (compared to one which was only slightly negative for the LZ specification).

Although the generalized-Leontief $\pi(p^*,w,v,t)$ and our earlier model are not nested in a classical statistical sense, they can be compared using nonnested hypothesis testing procedures. Our approach to this problem was to consider an artificial-regression model described by the following system of equations:

$$y = (1-\varsigma)\, y_\pi + \varsigma\, y_G$$

$$x_i = (1-\vartheta_i)\, x_{i\pi} + x_{iG}\vartheta_i$$

for i = 1, ... , n. Here subscript π refers the supply or demand function that would be generated by the generalized-Leontief $\pi(p^*,w,v,t)$ while subscript G refers to the supply or demand function that would emerge from our model. A nonnested hypothesis test that corresponds to the single-equation J-test for the correctness of the generalized-Leontief version of the technology would be to test that $\varsigma = \vartheta_i = 0$ for all i. As with the standard J-test, the above model will not generally be identified. Therefore, we substituted estimates of supply and demands derived from our model for y_G and for x_{iG} (as appropriate) before reestimating this model using Zellner's seemingly unrelated regression method. (Under the hypothesis that the G-system is appropriate, this estimation procedure is consistent.) We used a joint F test to test the null hypothesis that $\varsigma = \vartheta_i = 0$ for all i. The computed value of the joint F statistic was 17.938 and its p-value was 0.0001, leading us to reject this hypothesis at all reasonable levels of significance. We also estimated a version of the model where ς and $\vartheta_i (i = 1, \ldots, n)$ were all set equal to μ. The non-nested test then became a test of whether $\mu = 0$. The null hypotheses that $\mu = 0$ was rejected at all traditional levels of significance. Thus, we find no statistical reason to prefer the conventional specification to the generalized LZ model.[5]

Final Remarks

The principal debates over pesticide policy hinge critically on productivity issues. The extent to which pesticide use ought to be curtailed to protect human health and the environment depends on the extent to which food and fiber production would fall. Whether taxes should be used instead of direct regulation depends in part on the price responsiveness of pesticide demand, since governments tend to be reluctant to impose disproportionately large taxes. When and where restrictions on pesticide use will improve environmental quality overall depends in part on substitution between pesticides and other inputs.

To date, information on pesticide productivity and pesticide demand has been quite inadequate. Econometric methods have been used in only a handful of cases. Most analyses rely on assessments of crop production experts for information on alternative production systems and changes in crop damage, despite the fact that these assessments estimate average rather than marginal productivity, do not take into account adjustments by individual farmers, are subject to political biases, and have often proven wrong in retrospect.

LZ proposed an approach to estimating pesticide productivity econometrically that captures the fundamental biological role of pesticides and permits indirect estimation of crop damage. We generalize the LZ approach while enhancing its flexibility, and illustrate the new methodology with an application using data on aggregate U.S. agricultural production. The advantages of this new methodology are an ability to recapture pest damage directly from observed data and a great increase in the ability to model the production technology flexibly.

Our analysis uses time-series data for the entire United States. Thus, our actual empirical results should be interpreted with caution. Disaggregating this data by crop types and/or regions would permit a decisive analysis of damage differences and price elasticities by crop and/or region. Comparing abatement functions obtained from cross-sectional data at different points in time would allow analysis of changes in abatement technology due to the spread of resistance or other factors. Thus, considerable scope exists for future applications of our methodology.

Footnotes

1. In contrast to the LZ formulation (p. 264), the cost of abatement is a nonlinear function of g. Standard duality results ensure that the cost of abatement is linear in g if and only if G(z) is positively linearly homogeneous. In the case of a scalar input, linearity of the cost of abatement in g implies a linear abatement function. Both linearly homogeneous and linear abatement functions are inconsistent with g lying between 0 and 1, which in turn derives from the biological restriction that damage cannot exceed potential output.

2. We follow previous econometric work on pesticide productivity--as well as agricultural production generally--in treating production using a static framework (except for including a time trend to capture technological change). We ignore interseasonal dynamic considerations such as the spread of resistance (see for example Regev, Shalit and Gutierrez; Lazarus and Dixon) as well as intraseasonal pest population dynamics and pest-crop interactions. Clark and Carlson present evidence indicating that resistance has had statistically indiscernible effects in weed control, which accounts for the bulk of aggregate pesticide use in the U.S., as well as in disease control; thus, the effects of ignoring resistance should be small. Blackwell and Pagoulatos propose an alternative damage control specification, but it is valid for the case of a single pest without predators or competitors and in which pesticides are applied only once and all other inputs are applied only at planting time--conditions that are too restrictive for a characterization of aggregate U.S. agricultural production.

3. All equations were estimated under the assumption that all the time series involved were stationary. As a reviewer points out, this may be implausible. If the time series are not stationary, the resulting estimates could be seriously flawed. However, our model is highly nonlinear. Hence, recent developments in cointegration analysis are not applicable to our problem. Thus, like other researchers using these and similar data, we ignore the implications of potential nonstationarity. At some point, when the theory of nonlinear cointegrated relations has been more fully developed, it would be interesting to reexamine our model using such new techniques.

4. For a related approach to obtaining biological data from market data, see Chambers and Strand.

5. Because the LZ model is estimated in a stepwise fashion, no analogous single-regression test for whether the LZ is to be preferred to the conventional model exists. However, the overall poor performance of the generalized-Leontief $\pi^*(p,w,v,t)$ in terms of its economic properties seems to rule it out as a plausible alternative to the LZ which has much better economic properties.

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Table 1: Parameter Estimates for the Exponential and Logistic Abatement Specifications				
Parameter	Exponential		Logistic	
	Estimate	Standard Error	Estimate	Standard Error
λ/ψ	3.075606	0.24922	3.393526	0.26276
α/θ	-2.665343	0.04658	-2.612253	0.05125
a_p	12.902561	2.028708	12.856560	2.031720
b_{pL}	-5.041100	1.933796	-4.949614	1.944650
b_{pF}	-5.353494	0.695796	-5.345073	0.696839
b_{pM}	-2.160809	2.528963	-2.193738	2.532546
b_{pK}	-6.373086	1.759182	-6.346542	1.760405
b_{LL}	-1.769652	1.473930	-1.830444	1.482574
b_{LF}	0.693290	0.406854	0.685814	0.408288
b_{LM}	-3.279458	1.164158	-3.295743	1.166415
b_{LK}	0.434088	0.850212	0.401595	0.852718
b_{FF}	1.994731	0.248271	1.995001	0.248881
b_{FM}	0.064382	0.542684	0.065607	0.542725
b_{FK}	2.855737	0.269705	2.854909	0.269963
b_{MM}	1.859728	2.696463	1.896686	2.700412
b_{MK}	-0.949624	0.857806	-0.937498	0.857307
b_{KK}	1.548012	1.007063	1.535103	1.007653
τ_p	0.290269	0.017198	0.289385	0.017259
τ_L	0.035636	0.009837	0.036064	0.009900
τ_F	-0.027308	0.003000	-0.027263	0.003012
τ_M	-0.061367	0.009597	-0.061364	0.009634
τ_K	-0.042960	0.006271	-0.042788	0.006289

Table 2a: Short-run elasticities calculated at the sample mean					
price→ ↓quantity	Output	Labor	Fertilizer	Materials	Capital
Exponential Model					
Output	0.43348	-0.10478	-0.12348	-0.049807	-0.15541
Labor	0.31088	-0.43691	-0.04118	0.19438	-0.027220
Fertilizer	2.44248	-0.66209	-0.81532	-0.028231	-0.91136
Materials	0.16468	0.21661	-0.004719	-0.45016	0.07359
Capital	0.70093	-0.041377	-0.30206	0.10038	-0.45787
Logistic Model					
Output	0.43188	-0.10297	-0.12340	-0.050611	-0.15490
Labor	0.30551	-0.43499	-0.040675	0.19534	-0.025182
Fertilizer	2.44084	-0.66303	-0.81647	-0.028768	-0.91265
Materials	0.16734	0.21769	-0.004809	-0.45287	0.07265
Capital	0.69864	-0.038279	-0.30198	0.099098	-0.45748

Table 2b: Long-run elasticities calculated at the sample mean						
price→ ↓quantity	Output	Labor	Fertilizer	Materials	Capital	Pesticide
Exponential Model						
Output	0.54194	-0.11288	-0.13303	-0.05366	-0.16743	-0.06130
Labor	0.33491	-0.43871	-0.04323	0.19352	-0.02988	-0.01358
Fertilizer	2.63132	-0.28824	-0.83194	-0.03494	-1.34572	-0.10672
Materials	0.17741	0.21566	-0.00584	-0.45062	0.07218	-0.00720
Capital	0.75512	-0.04542	-0.30683	0.098456	-0.46387	-0.03063
Pesticide	2.70909	-0.20233	-0.23844	-0.09618	-0.30010	-1.53104
Abatement	0.07731	-0.00577	-0.00680	-0.00275	-0.00856	-0.04369
Logistic Model						
Output	0.54126	-0.11101	-0.13302	-0.05456	-0.16699	-0.06105
Labor	0.32935	-0.43675	-0.04277	0.19448	-0.02782	-0.01331
Fertilizer	2.63131	-0.28517	-0.83324	-0.03565	-1.34547	-0.10631
Materials	0.18040	0.21673	-0.00596	-0.45334	0.071207	-0.00729
Capital	0.75316	-0.04228	-0.30678	0.09713	-0.46350	-0.03043
Pesticide	2.69800	-0.19821	-0.23753	-0.09742	-0.29818	-1.50587
Abatement	0.07804	-0.00573	-0.00687	-0.00282	-0.00862	-0.04356

Table 2c: Long-run elasticities of the autocorrelation-corrected model, calculated at the sample mean						
price→ ↓quantity	Output	Labor	Capital	Materials	Fertilizer	Pesticide
Exponential Model						
Output	0.26346	-0.02512	-0.03529	-0.04007	0.04415	-0.05444
Labor	0.07453	-0.22356	-0.01326	0.13336	0.04153	-0.00339
Capital	0.15918	-0.02016	-0.24389	0.11957	0.01281	-0.00723
Materials	0.13250	0.14893	0.08766	-0.46160	0.11541	-0.00602
Fertilizer	-0.87337	0.27688	0.05616	0.69045	-0.30106	0.03968
Pesticide	2.40608	-0.05043	-0.07086	-0.08045	0.08864	-0.60271
Logistic Model						
Output	0.25973	-0.02947	-0.03328	-0.04233	0.04393	-0.05635
Labor	0.08743	-0.22669	-0.01568	0.12864	0.04083	-0.00412
Capital	0.15011	-0.02383	-0.23815	0.12245	0.01438	-0.00708
Materials	0.13996	0.14336	0.08977	-0.46055	0.11522	-0.00660
Fertilizer	-0.86902	0.27220	0.06305	0.68932	-0.30001	0.04099
Pesticide	2.49016	-0.06142	-0.06938	-0.08824	0.09158	-0.67038

Table 3: Parameter estimates for the conventional generalized-Leontief system

Parameter	Estimate	Standard Error
b_{PP}	9.053506	1.986584
b_{PL}	-2.414691	1.740267
b_{PK}	-3.325207	1.676242
b_{PM}	1.612477	2.368800
b_{PF}	-3.477347	0.648827
b_{PZ}	-2.315334	0.605846
b_{LL}	-1.329611	0.671525
b_{LK}	-0.691577	0.781885
b_{LM}	-4.398103	1.101933
b_{LF}	-0.186491	0.388425
b_{LZ}	0.733905	0.377803
b_{KK}	0.269366	0.480258
b_{KM}	-2.278713	0.873705
b_{KF}	2.035254	0.266377
b_{KZ}	0.490050	0.242991
b_{MM}	-0.371563	1.258498
b_{MF}	-0.480209	0.545155
b_{MZ}	0.621291	0.469572
b_{FF}	0.540985	0.138836
b_{FZ}	0.704698	0.163632
b_{ZZ}	0.230289	0.089484
τ_P	0.262179	0.015497
τ_L	0.045319	0.008953
τ_K	-0.032944	0.005928
τ_M	-0.044468	0.009423
τ_F	-0.018561	0.003025
τ_Z	-0.020493	0.003006

Table 4: Long-run Elasticities of the generalized-Leontief Model Calculated at the Sample Mean						
price→ ↓quantity	Output	Labor	Fertilizer	Materials	Capital	Pesticide
Output	0.23705	-0.05125	-0.08190	0.03795	-0.08280	-0.05906
Labor	0.15205	-0.04200	0.01106	0.26068	0.04337	-0.04714
Fertilizer	1.62001	0.07374	-0.06253	0.21057	-0.94417	-0.33486
Materials	-0.12549	0.29050	0.03520	-0.32748	0.17659	-0.04932
Capital	0.37344	0.06592	-0.21528	0.24087	-0.40882	-0.05614
Pesticide	2.60989	-0.70215	-0.74816	-0.65918	-0.55006	0.04966

Figure 1: Maximum, Minimum and Actual Supply with Exponential Damage

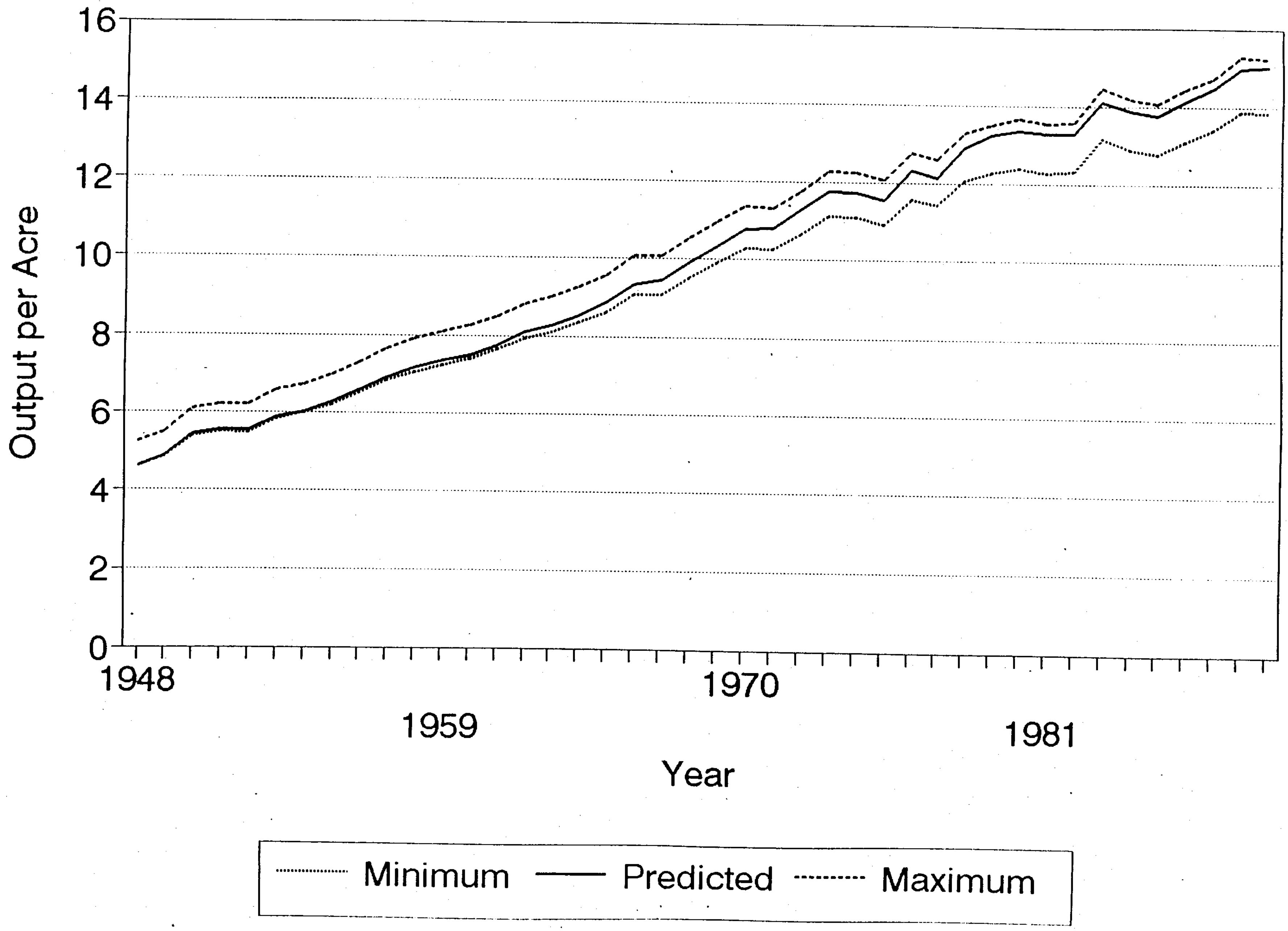

Figure 2: Maximum, Minimum and Actual Supply with Logistic Damage