III. ECONOMETRIC ESTIMATION OF PESTICIDE PRODUCTIVITY

A. INTRODUCTION

Econometric estimates of pesticide productivity can be of tremendous importance in regulatory decision-making. The estimates of aggregate pesticide productivity obtained by Headley, Campbell, Carlson and others showing values of marginal pesticide productivity several times greater than marginal cost have been used many times to underscore the importance of pesticides to the U.S. agricultural economy. Estimates of county- or state-level patterns of substitution among pesticides and pest management strategies and of the productivity effects of these substitutions can be helpful in giving regulators a good sense of the likely effects of alternative regulatory actions. While such econometric estimates are likely to be less accurate than simulation-derived estimates regarding any specific pesticide, they are also likely to be more robust and transferable regarding broad classes of pesticides and are thus especially useful as a tool for giving regulators a "first-cut" sense of the likely effects of regulation in a relatively rapid, cheap manner.

Econometric methods have not been used to obtain these kinds of estimates despite these advantages. Problems of data availability are one reason for this failure to use econometric methods. Another reason, though, may be the counterintuitive, counterfactual results obtained by the econometric investigations performed to date. As we mentioned above, these studies have consistently found average values of marginal pesticide productivity several times greater than marginal cost, suggesting that pesticides are underutilized in U.S. agriculture. Most biologists, economists and regulators believe the opposite to be true and may be disinclined to use econometric methods on these grounds. During budget period 1, we investigated the conceptual foundations of these econometric studies and found that the standard production function specifications used by Headley and others produce estimates of pesticide productivity which are biased upwards, that is, overestimate pesticide productivity. We pointed out that pesticides play a different role in production than normal inputs such as water, fertilizer, etc., in that they do not augment crop growth. Rather, pesticides are damage control inputs, whose use prevents crop loss. As a result, pesticide productivity should not be modeled in the same way as normal inputs. We developed a production function specification which incorporates damage control explicitly; a number of examples used entomologically-derived pesticide "kill" functions were developed and their estimation discussed.

During budget period 2 on work in this area proceeded along two lines. First, we revised our original paper for publication in the American Journal of Agricultural Economics, where it will appear in May 1986. The revised paper is presented in Section B. Second, we applied the production function specification we developed to data on cotton production in the San Joaquin Valley, California. The results of these efforts are presented in Section C. Section D considers some possible further research along these lines.

B. THE ECONOMETRICS OF DAMAGE CONTROL: WHY SPECIFICATION MATTERS[1]

One of the most important classes of factors of production is that consisting of damage-control agents. Unlike standard factors of production (land, labor, and capital), these inputs do not increase (they may, in fact, decrease) potential output. Instead, their distinctive contribution lies in their ability to increase the share of potential output that producers realize by reducing damage due to both natural and human causes. Many of the innovations in agriculture over the past few decades have involved the introduction of damage-control agents, e.g., pesticides, windbreaks, sprinklers for frost protection, immunizations and antibiotics in feedlot operations, etc. Advances in storage technology (for instance, the fumigation of stored grains) have hinged on improvements in damage-control agents. Other important examples of damage-control agents include the use of smoke alarms and sprinkler systems to reduce fire damage, antitheft/antivandalism measures (in fact, the prevention of crimes against property is essentially an exercise in damage control), etc.

The use of damage-control agents also tends to subject producers to certain difficulties which do not arise in connection with the use of standard inputs. The most important problem is that, in many cases, the damaging agents involved (be they human, insect, or weed) adapt to the damage-control measures taken as time passes, rendering the latter increasingly ineffective, This problem of growing resistance to damage control has important economic ramifications.

In many situations, notably those involving natural systems (e.g., pest control, immunization, etc.), the ability of simulation methods to deal with multiple dynamic processes makes them better suited for exploring the details of optimal damage-control strategies. In positive studies, however, where the aim is to explain observed behavior and to estimate behavioral or physical parameters, econometric methods are generally required. The computational complexities and data requirements of econometric methods restrict them to specifications that are simpler and less detailed than the ones used for simulations. Thus, econometric methods are inevitably confined to a lower level of precision than simulation models. The key to maximizing the accuracy and information content of econometric models lies in incorporating as much as possible the critical elements of the available scientific knowledge without fatally compromising their generality and estimatability.

To date, econometric investigations of damage control have tended to rely on generic econometric models rather than to draw on knowledge about the actual physical or biological processes involved to specify the relevant functional forms. Specification errors arising in this way may generate biases of considerable size in estimates of productivity and, hence, faulty conclusions about efficient input usage.

Economic analysis of agricultural pesticide use is a prime example of this phenomenon. Theoretical (Feder and Regev; Regev, Shalit, and Gutierrez) and normative empirical (Shoemaker; Regev, Gutierrez, and Feder; Talpaz and Borosh; Regev, Shalit, and Gutierrez) models of pest management at the farm or regional level have incorporated the available entomological knowledge in their model specifications and have derived optimal management patterns and policy recommendations on this basis. By contrast, econometric measurements of pesticide productivity have been derived from standard production theory models, notably using Cobb-Douglas specifications. It will be shown that productivity estimates are flawed conceptually and, as a result, contain significant statistical biases.

Presented first is a general discussion of the role of damage abatement in the production process. It is argued that damage-control inputs should be incorporated into production analysis in a different manner than regular inputs; in fact, models of biological and physical processes are tapped to obtain specifications of production processes with damage control inputs. These specifications are especially appropriate for production analysis at the microlevel, i.e., the individual firm, the farm, or even the field. Heterogeneity among producers and variation in environmental conditions may mean that proper aggregation procedures should be incorporated to derive specifications appropriate for microlevel regional analysis (Zilberman).

This approach to the specification of the role of damage-control agents in production has two important implications for theoretical and, especially, empirical work. First, it is shown that the types of production function specifications used most commonly to estimate factor productivity overestimate the productivity of damage-control inputs even in large samples. The source of this upward bias is a misspecification of the shape of the marginal factor productivity curve of damage-control inputs which decrease more rapidly in the economic range than standard specifications impose.

The kind of specification proposed for incorporating damage-control agents into production analysis produces empirical models in which factor productivity can be estimated easily from existing data in a number of important instances. Specifications will be derived and estimation procedures will be discussed for several cases of special interest with respect to pesticides.

The second important characteristic of this specification is the way it handles changes in damage-control agent productivity over time. In the case of pesticides, for example, the spread of resistance through a pest population is an important problem. Treating a damage-control agent, such as a pesticide, in the same way as an ordinary factor of production has led economists to predict behavior contrary to observed fact. In a standard production function, decreasing factor effectiveness is reflected in decreasing marginal factor productivity and, thus, in reduced levels of factor use. In the specification, decreasing effectiveness may increase factor demand; this is precisely the phenomenon observed in pesticide use trends.

A Model of Damage Control

Damage-control agents do not enhance productivity directly as do the standard types of production factors. To the contrary, they may even impede productivity somewhat: The application of a pesticide, for example, may be harmful to crop plants to a certain extent. Their contribution to production may be understood best if one conceives of actual (realized) output as a combination of two components: potential output (the maximum quantity of product obtainable from any given combination of inputs) and losses caused by damaging agents (insects, weeds, bacteria, fire, floods, and vandals) present in the environment. These losses, in turn, are a function of the environmental conditions determining the destructive capacity of the relevant damaging agents and of the action of damage-control agents on that destructive capacity through the damage-abatement efforts undertaken. Thus, the productivity of damage-control agents should be defined in terms of their contributions to damage-abatement services, that is, the abatement effort (hereafter referred to simply as abatement). It should be clear that damage and, hence, abatement are necessarily limited by two factors: potential output and the destructive capacity of the damaging agents. Damage can be at most equal to potential output and no smaller than zero, and abatement can be at most equal to total destructive capacity (implying that production will equal some minimum value) and no smaller than zero (implying that production will equal potential output). This suggests that abatement should be defined in terms of its impact on the destructive capacity of the relevant damaging agents since it affects damage and production via that impact. For example, pest management efforts aim to limit crop losses by reducing the sizes of pest populations at critical times of the year; vaccination programs reduce susceptibility to infection; fire safety efforts,(installation of sprinkler systems and fire escapes and use of fire-retardant materials) reduce the damages sustained from any given type of fire, etc.

These restrictions on abatement can be captured with no loss of generality by defining an abatement function G(X) as the proportion of the destructive capacity of the damaging agent eliminated by the application of a level of control agent X. For the case of pest managment, for example, this means that abatement will be measured by the proportion of the target pest population killed by the application of a given amount of pesticide, that is, by what is commonly called the pesticide effectiveness or kill function. This definition suggests that the abatement function will possess the properties of a cumulative probability distribution: It will be defined on the (0, 1) interval with G = 1 denoting complete eradication of the destructive capacity and G = 0 denoting zero elimination, i.e., maximum destructive capacity; it will be monotonically increasing; and it will approach a value of unity as damage-control agent use increases, i.e., $G(X) \to 1$ as $X \to \infty$. The derivative of G with respect to X, $G_X(X) = g(X)$, represents marginal damage-control agent effectiveness or marginal productivity; it is simply the density of G(X).

In this paper, X will be treated as a simple input for the sake of simplicity; however, it should be noted that X will often be a vector of inputs defined by time of application. In many situations, there are multiple damaging agents and a variety of damage-control inputs to use; moreover, timing of intervention will affect damage-control effectiveness. In econometric work, of course, the dimensionality of X will be limited by the data available. It should also be noted that G will generally be a function of variables other than damage-control inputs, for example, state variables which indicate exogenous factors such as pest prevalence, fire danger, weather conditions, etc. However, damage-control variables are the only controllable factors affecting abatement effort. For this reason, the analysis will concentrate on their role and will ignore.the exogenous factors.[2] Similarly, the analysis will examine the case of a single destructive agent (single abatement effort) where G has scalar values. In many situations, a firm may have to deal with several sources of damage each of which requires some abatement. Analysis of the more general case is beyond the scope of this paper; however, most of the results obtained here carry over to the more general case. One interesting aspect of the general case is that some damage-control agents may enter into several types of abatement.

It follows from the characterization of actual output as a combination of potential output and losses that production, Q, can be characterized as a function of directly productive inputs, Z, and damage abatement G(X):

(1) $$Q = F[Z, G(X)].$$

The production function $F(\cdot)$ will be assumed to possess the standard properties of production functions, notably concavity in (Z, G). When the destructive capacity of damaging agents is completely eliminated, losses will be zero and actual output will equal potential output, that is, potential output can be expressed as F(Z, 1). When G = 0, F(Z, 0) denotes the output obtainable under maximum destructive capacity, i.e., the minimum actual output.

The generality of $F(\cdot)$ allows damage abatement to affect actual output in a variety of ways. For example, a general linear form, $Q = F_1(Z) + F_2(Z)\,G(X)$ may be reasonable in a variety of situations. The function $F_1(Z)$ represents minimum output in this case, while $F_1(Z) + F_2(Z)$ represents potential output. This general linear form encompasses some commonly used specifications as subcases: Setting $F_1(Z) = 0$ implies that actual output is proportional to abatement; setting $F_2(Z)$ equal to a constant implies additive separability of potential output and losses. However, output may also be nonlinear in abatement. In pest management, for instance, one would expect to find decreasing marginal productivity of abatement since further reductions in damages tend to decline as pest populations get smaller.

There are two ways of determining the optimal level of damage-control agent use: (1) one can solve for the profit-maximizing choice of X directly or (2) one can employ a two-step procedure involving, first, the profit-maximizing choice of abatement, G, and, second, the choice of X to attain this optimal level of abatement at least cost. Analyzing the choice of optimal abatement is of interest in its own right. Moreover, because the choices of abatement and damage-control agent use are often confused, it is instructive to examine the differences and relationships between the two.

Consider first the optimal choice of abatement, G. One can view this choice as the intermediate step in the two-step procedure discussed above, or as the purchase of abatement services as a marketed commodity which is not unusual in pest control, property protection, and other stiuations. Let s denote the price of a unit of abatement; p denote the price of the product, Q; and r denote the price of the normal input, Z.

The relevant maximization problem is

$$\max_{Z,G} \Pi = pF(Z, G) - rZ - sG. \tag{2}$$

Assuming an interior maximum and denoting derivates with subscripts, the necessary conditions for maximization are given by

$$pF_Z = r, \ pF_G = s. \tag{3}$$

Sufficiency is assured by the negative semidefiniteness of the Hessian matrix which implies $F_{ZZ} \leq 0$, $F_{GG} \leq 0$, and $F_{ZZ}F_{GG} - F_{GZ}^2 \geq 0$. The elasticity of demand for damage abatement, G, found by differentiation of (3) with respect to s, is

$$\frac{s}{G} G_s = \frac{1}{\dfrac{F_{GG}G}{F_G} - \dfrac{\left(F_{GZ}\right)^2 G}{F_G F_{ZZ}}} = \varepsilon_G. \tag{4}$$

Now consider the optimal choice of damage-control agent use. Letting w denote the price of the damage-control agent, the relevant profit-maximization problem is

$$(5) \qquad \max_{Z,X} \Pi = pF[Z, G(X)] - wX - rZ$$

and the necessary conditions are

$$(6) \qquad pF_Z = r, \; pF_G \, g = w.$$

Sufficiency is ensured by the negative semidefiniteness of the Hessian matrix which implies $F_{ZZ} \leq 0$, $F_{GG} \cdot g^2 + F_G \cdot g' \leq 0$, and $F_{ZZ}(F_{GG} \cdot g^2 + F_G \cdot g') - F_{ZG} \, 1 \, g^2 \geq 0$; both the marginal productivity of damage abatement, F_G, and the marginal effectiveness of the damage-control input, g, must be declining to ensure that a maximum has been attained. The elasticity of demand for the damage-control input is

$$(7) \qquad \varepsilon_X = \frac{w}{X} X_w = \frac{1}{\frac{\eta_G}{\varepsilon_G} + \eta_g},$$

where $\eta_G = gX/G$ is the elasticity of abatement and $\eta_g = g_X X/g$ (the elasticity of the marginal effectiveness of the damage-control input) measures the curvature of the damage abatement function.

Evaluation of the expression on the right-hand side of (7) allows one to draw several conclusions about the qualitative characteristics of demand for damage-control agents and its relationship to the demand for abatement.

First, because g(X) has the properties of a probability density, it is reasonable to assume that $|\eta_g| > 1$, that is, that the marginal effectiveness curve is always elastic. The existence of a finite abatement function (probability distribution), $G(X)$, defined on $0 \leq X \leq \infty$ is assured if the marginal effectiveness curve (density function), $g(X)$, is declining faster than $1/X$ (since $\int 1/X = \ln X$, which does not converge as $X \to \infty$) which implies that $g_X(X)\, X/g(X) < -1/g(X) < -1$, a property which is easily verified for any of the commonly used distributions (normal, gamma, etc.). As a result of this property of $g(X)$, it is obvious from (7) that $|\varepsilon_X| < 1$; i.e., the <u>demand for damage-control inputs is everywhere inelastic</u> in all practical instances.

Second, it is evident from (7) that the demand for abatement (represented by its elasticity ε_G) influences the demand for damage-control inputs. However, the extent of this influence varies considerably. Consider first the case where $\varepsilon_G = 0$, that is, where the demand for damage abatement is perfectly inelastic. Rearrangement of (7) produces the relation $\varepsilon_X = \varepsilon_G/(\eta_G + \eta_g\, \varepsilon_G)$, from which it is evident that $\varepsilon_X = 0$ whenever $\varepsilon_G = 0$; that is, that the demand for damage-control agents is perfectly inelastic whenever the demand for abatement is perfectly inelastic. <u>Whenever the demand for abatement is perfectly inelastic, then the demand for damage-control agents will be dominated by the demand for abatement</u>.

One situation where this may occur is when the relevant production function exhibits fixed proportions with respect to abatement. Another is the case where abatement exhibits threshold effects such as where some positive proportion of damage is equivalent to total loss of the crop. For example, U. S. Food and Drug Administration regulations prohibit the sale of shipments of apples in which more than 3 percent have been found to be wormy; here abatement of 96 percent is equivalent to none, while 97 percent passes muster. (Similar regulations govern the sale of most produce.) In this case, all that matters to the grower is that worm infestations affect no more than 3 percent of the crop; hence, the demand for pesticides to control this problem will be perfectly inelastic at the 5 percent abatement level.

In the case where the demand for abatement is not perfectly inelastic--where $|\varepsilon_G| > 0$--it is easy to verify that $\partial\varepsilon_X/\partial\varepsilon_G = \eta_G/(\eta_G + \eta_g\ \varepsilon_G)^2 > 0$, i.e., that the elasticity of the demand for abatement has a positive effect on the elasticity of demand for damage-control inputs. Therefore, the more elastic the demand for abatement is, the more elastic the demand for damage-control inputs will be.

As the level of damage-control agent use rises, however, η_G declines (since $\partial\eta_G/\partial X = [1 - \eta_G + \eta_g]\ \eta_G/X$) and, hence, the influence of the demand for abatement, ε_G, on the demand for damage-control inputs, ε_X, tends to diminish. In fact, as X gets sufficiently large that G(X) approaches 1, η_G tends to vanish; as a result, ε_X approaches $1/\eta_g$. Since in most observed cases damage-control agents tend to be used at close to full effectiveness, one can conclude that, whenever $|\varepsilon_G| > 0$, the elasticity of demand for damage-control inputs is the reciprocal of the elasticity of the marginal effectiveness curve.

Econometric Implications of the Specification

What happens when a standard production function specification, such as a Cobb-Douglas, is used to estimate the marginal productivity of damage control? The result of such a misspecification can be seen in figure 1 which compares a standard Cobb-Douglas marginal productivity curve with one derived from the damage-control specification proposed above. It is easily seen that

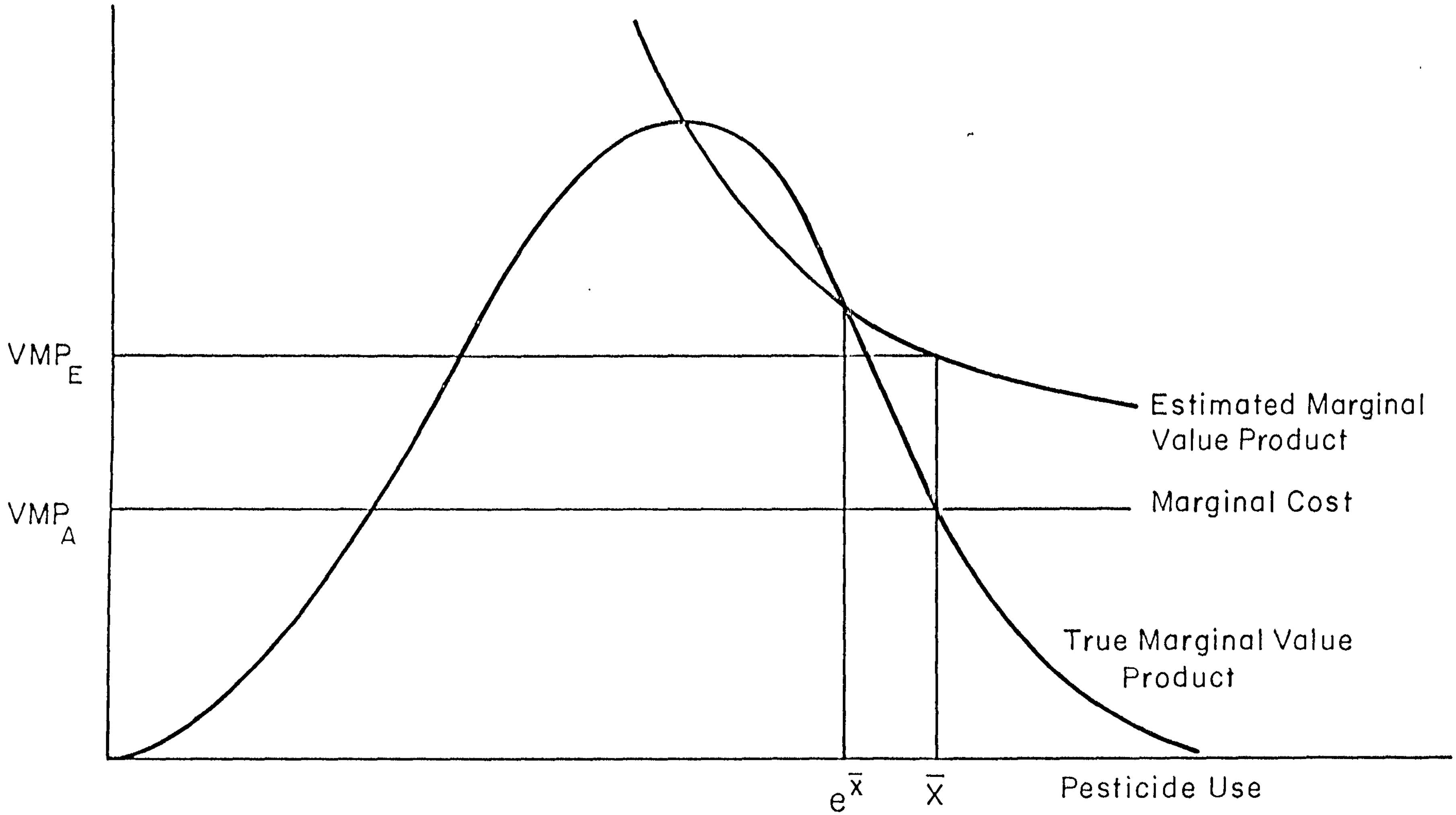

FIGURE I. The Impact of Misspecification on Damage Control Agent Productivity Estimates

any specification which restricts the rate at which the marginal effectiveness curve declines will tend to produce overestimates of the marginal productivity of damage-control agents and, at the same time, to produce underestimates of the productivity of natural factors. Moreover, these biases will occur even when the specification used is a good approximation of the true model in every respect but the incorporation of the damage-control input.

More formally, assume that the output elasticities of abatement, G, and of all other inputs, Z, are constant and that the elasticities of substitution differ only negligibly from one over the relevant range; then the Cobb-Douglas specification,

$$Q = e^{\alpha} Z^{\beta} [G(X)]^{\gamma} e^{u}, \tag{8}$$

represents the underlying production function and the random error associated with it.[3] It will be convenient to use the logarithmic form of the model. Letting the lower case letters, q, z, and x, represent the natural logarithms of Q, Z, and X, respectively, the model can be rewritten:

$$q = \alpha + z\beta + \gamma \ln G(X) + u. \tag{9}$$

Now suppose that, instead of the model given by (8) and (9), a Cobb-Douglas specification using the damage-control agent, X, instead of abatement, G(X), is used to estimate this; that is, that the estimating model used is

$$q = \alpha + z\beta + \gamma x + v. \tag{10}$$

As we show formally in the Appendix, the ordinary least-squares (OLS) estimation of α, $\hat{\alpha}$ converges in probability to a number less than α; specifically,

$$\operatorname*{plim}_{n\to\infty} \hat{\alpha} = \alpha + \gamma\,[\ln G(e^{\bar{x}}) - \eta_G(e^{\bar{x}})\,\bar{x}] < \alpha, \tag{11}$$

where $\bar{x}$ is the mean value of ln(X). At the same time, the OLS estimation of γ, $\hat{\gamma}$, converges in probability to a number which is greater than the measure of damage-control agent productivity at mean usage level $\bar{X}$, $\eta_G(\bar{X})\,\gamma$:

$$\operatorname*{plim}_{n\to\infty} \hat{\gamma} = \eta_G(e^{\bar{x}})\,\gamma > \eta_G(\bar{X})\,\gamma. \tag{12}$$

The implication of these findings is that the use of a standard Cobb-Douglas specification to estimate damage-control agent (pesticide) productivity leads to overestimation of the marginal productivity of the damage-control agent and underestimation of the marginal productivity of natural and omitted factors even when the Cobb-Douglas specification is good for abatement.

The intuition behind these results can be grasped easily upon examination of figure 1. The specification of damage-control agent productivity proposed here suggests that the marginal product (marginal effectiveness) curves of the damage-control agent will decline at an increasing rate in the economic region. The reason for this increasingly rapid decline lies in the specification of marginal effectiveness as a probability density: To converge, g(X) must decline faster than 1/X and, hence, must decrease more rapidly as X gets larger. As a result, the elasticity of the marginal effectiveness curve also grows as X increases. A specification like the Cobb-Douglas cannot match this behavior. Instead, a standard Cobb-Douglas specification will produce a marginal effectiveness curve whose elasticity is constant and, hence, which declines more slowy than the true marginal effectiveness curve. The implications of this fact can be seen easily in figure 1. The standard Cobb-Douglas specification will produce consistent estimates of the damage-control agent productivity parameter $\eta_G \gamma$ at a point $e^{\bar{x}}$ which necessarily lies to the left of the average level of damage-control agent use $\bar{X}$. Since the true parameter tends to decline quite rapidly, the estimated marginal product curve will lie above the true curve for levels of control agent use greater than $e^{\bar{x}}$. At average use levels then, the estimated value of marginal damage-control agent productivity (VMP_E) will be greater (conceivably substantially greater) than the true value of marginal damage-control agent productivity (VMP_A) and will appear to be greater than marginal control agent cost (MC).[4]

This result explains one of the most perplexing findings of the econometric literature on pesticide use: that marginal pesticide productivity has been well above marginal application cost. Perhaps the clearest example is the work of Campbell, who applied a Cobb-Douglas production function to data on output, pesticide use, and other factors in Canadian apple orchards and found marginal pesticide productivities that were about 12 times marginal cost. The implication, of course, is that pesticides are greatly underutilized. In light of the biological and behavioral literature on pesticide use, such a conclusion is astounding, to say the least. The overwhelming consensus opinion of the theoretical, normative empirical, and casual empirical studies performed concerning pesticide use is that pesticides are overused rather than underutilized as the econometric literature suggests. Consideration of such factors as the potential growth of resistance, common stock externalities, informational and human capital problems, and the like suggests that marginal pesticide productivity lies below marginal cost at common usage levels.

The analysis of econometric method presented above indicates that the source of this contradiction is the incorrect methodology employed in these studies. Estimation of the production function using the damage-control agent (pesticide) instead of an abatement effectiveness (kill) function produces an upward bias in the estimates of damage-control agent (pesticide) which, in turn, implies the productivity underutilization of the damage-control agent.

Estimating Damage Control: Some Sample Specifications

Because the abatement function can be represented quite naturally by a cumulative distribution, it is not difficult to specify empirical models for estimating the productivity of damage-control agents. In this section we give some examples of possible specifications derived from distributions that have been used in the pest management literature. It turns out that, in a number of important cases, estimation of the parameters of these models is remarkably simple so that use of abatement functions in empirical work entails little or no additional cost.

Since the Cobb-Douglas specification is used so commonly, assume that the modified Cobb-Douglas form given by (8) represents the production function well. Under this assumption and the assumption of a specific form for the abatement function G(X), it becomes possible to derive production function and damage-control agent demand function specifications for use in econometric work. Table 1 shows the production functions (in log form) and damage-control agent demand functions implied by four specifications of G(X): the Pareto distribution, the exponential distribution, the logistic distribution, and the Weibull distribution. The latter three specifications are of particular interest because of their use in this capacity in normative empirical models

Table-1. Alternative Econometric specifications

Distribution	G(X)	Production function	Damage control agent demand
Pareto	$1 - K^{\lambda} X^{-\lambda}$	$q = \alpha + z\beta + \gamma \ln [1 - K^{\lambda} X^{-\lambda}]$	$K^{\lambda} X^{-\lambda} [w + \lambda\gamma pQX^{-1}] = w$
Exponential	$1 - e^{-\lambda X}$	$q = \alpha + z\beta + \gamma \ln [1 - e^{-\lambda X}]$	$X = \frac{1}{\lambda} \ln \left[1 + \frac{\lambda\gamma pQ}{w}\right]$
Logistic	$+ \exp \{\mu - \sigma X\}]^{-1}$	$q = \alpha + z\beta - \gamma \ln [1 + \exp \{\mu - \sigma X\}]^{-1}$	$X = \frac{\mu}{\sigma} + \frac{1}{\sigma} \ln \left[\frac{pQ}{w} - \frac{1}{\gamma\sigma}\right]$
Weibull	$1 - \exp \{-X^{c}\}$	$q = \alpha + z\beta + \gamma \ln [1 - \exp \{-X^{c}\}]$	$X = \frac{1}{c} \ln \left[c\gamma X^{c-1} \frac{pQ}{w} + 1\right]$

of pest management. The Pareto, on the other hand, is of interest primarily because of its econometric implications.

Consider first the case of the Pareto abatement function. In the form given in table 1, both the production function and damage-control agent demand relation are quite intractable for linear estimation and must be approached by nonlinear means. But in the special case where $\gamma = 1$, that is, abatement is proportional to potential output, it can be shown that the supply function can be expressed as

$$Q = a_0 \, p^{a_1} \, r^{a_2} \, w^{a_3} \tag{13}$$

where $a_0 = [e^{2\alpha+\lambda} \, \beta^{\beta/(1+\lambda)} \, \lambda K^{\lambda}]^{1/[1+\lambda-\beta(2+\lambda)]}$; $a_1 = [1 + \beta(2 + \lambda)]/[1 + \lambda - \beta(2 + \lambda)]$; $a_2 = -[1 + \beta(2 + \lambda)]/[1 + \lambda - \beta(2 + \lambda)]$; and $a_3 = -1/[1 + \lambda - \beta(2 + \lambda)]$. Similarly, demand for the damage-control agent can be expressed as:

$$X = a_0 \, p^{a_1} \, r^{a_2} \, w^{a_3} \, Q^{a_4} \tag{14}$$

where $\bar{a}_0 = [\lambda e^{\alpha} \, K^{\lambda}]^{1/(1+\lambda)}$, $a_1 = (1 + \beta)/(1 + \lambda)$, $a_2 = -\beta/(1 + \lambda)$, $a_3 = -1/(1 + \lambda)$, and $a_4 = \beta/(1 + \lambda)$. In short, a Pareto damage abatement function, together with the assumption of abatement proportional to potential output, yields standard Cobb-Douglas specifications for the supply function and for damage-control agent demand. It turns out that this result arises from the fact that the Pareto distribution, like the Cobb-Douglas, possesses a marginal curve (density) elasticity which is constant. For the form of the Pareto distribution given here, for instance, it is readily apparent that the marginal effectiveness curve, $g(X) = \lambda K^{\lambda} X^{-(\lambda+1)}$ has an elasticity of $-(\lambda + 1)$ for X. The Pareto distribution is exceptional in this regard: The density elasticities of most distributions increase relatively rapidly. In fact, the Pareto distribution can be considered a limiting case for probability distributions in this respect.

While this demonstration shows that the standard Cobb-Douglas specification may be valid for examining the role of damage-control agents in production under some conditions, it turns out that these conditions are so restrictive as to be unimportant practically. The validity of a standard Cobb-Douglas specification depends on two conditions: (1) that abatement be proportional to potential output and (2) that abatement be well represented by a Pareto distribution. Condition (1) is certainly a good description of abatement in many situations; it should be recognized, however, that there are also many situations where it does not characterize the role of abatement well. Condition (2) may also hold in some cases. But, by and large, Pareto distributions have not been found to characterize abatement very well precisely because of their slow rates of change. (The distributions used for pesticide effectiveness, for example, are discussed in detail below.)

Now consider the case where the abatement function is assumed to be exponential. (In the pesticide literature, this specification was used by Regev, Gutierrez, and Feder in their study of alfalfa weevil control.) The production function is nonlinear in λ. It can be estimated, of course, by nonlinear methods or, since λ should lie between zero and one, the parameters of the model can be estimated by linear techniques combined with a grid search for λ.

Alternatively, consider the demand for the damage-control agent. A slight rearrangement of the relation given in table 1 yields a function of the form:

$$e^{X} = a_0 + a_1\left(\frac{pQ}{w}\right), \tag{15}$$

where $a_0 = 1 + e^{1/\lambda}$ and $a_1 = \lambda\gamma$. This relation is estimated easily using OLS methods because the right-hand side is a simple linear function of revenue and pesticide price, data for both of which, it is important to note, are generally available. The production function parameters of particular interest, γ and λ, are recovered easily from the estimated coefficients, a_0 and a_1.

Alternatively, assume that the abatement function can be represented by a logistic distribution as was done by Shoemaker in her study of flour moth control. As is evident from table 1, the demand function for the damage-control agent (pesticide) can be expressed as

$$X = a_0 + a_1 \ln\left[\frac{pQ}{w} - \frac{1}{\gamma\sigma}\right], \tag{16}$$

where $a_0 = \mu/\sigma + 1/\sigma \cdot \ln \gamma\sigma$ and $a_1 = 1/\sigma$. If $1/\gamma\sigma$ is sufficiently small, $\ln [pQ/W]$ can be use as a proxy for $\ln [pQ/W - 1/\gamma\sigma]$ at a cost of a negligible reduction in efficiency. In this case, use of a logistic abatement function implies that the proper specification of damage-control agent demand is as a linear function of $\ln [pQ/W]$.

This approximate demand relation can be estimated easily using OLS, and the parameter σ can be recovered from the estimate of a_1. In general, it will not be possible to recover estimates of the two remaining parameters γ

and μ. If, however, there is reason to believe that damage is strictly proportional to potential output, i.e., we believe that $\gamma = 1$, then estimation of both of the parameters of the abatement function can be estimated using the damage-control agent demand function.

As a final example, consider the case where the abatement function can be represented by a Weibull distribution as Talpaz and Borosh assume in their study of pest control in cotton. The demand of the damage-control agent is shown in table 1. In general, $c\gamma X^{c-1} (pQ/w)$ will be large enough to be a very close approximation to $c\gamma X^{c-1} (pQ/w) + 1$ so that the relation

(17) $$X = \frac{1}{c} \ln \left[c\gamma X^{c-1} \left(\frac{pQ}{w} \right) \right]$$

will be a good approximation to the demand function given in table 1. The relation in (17) can be rearranged to yield the demand function,

(18) $$X + \frac{c - 1}{c} \ln X = a_0 + a_1 \ln \left(\frac{pQ}{w} \right),$$

where $a_0 = (\ln c\gamma)/c$ and $a_1 = 1/c$. By and large, then, a Weibull damage abatement function implies that demand should be specified as the function in (18).

This demand relation is nonlinear in the parameters; hence, the parameters cannot be estimated by straightforward linear regression. It does seem, however, that a fairly simple iterative procedure could be used. The first stage of such a procedure would involve an OLS regression of $X + \ln X$ on a constant and $\ln [pQ/w]$; for reasonable values of c, $(c - 1)/c$ will be quite close to one so that $X + \ln X$ will be a good approximation for the left-hand side of (18). Estimates of c and γ can be derived easily from the estimates of

a_0 and a_1. The approximation error can be reduced by using the estimate of c obtained from such a regression to recalculate the left-hand side and redoing the OLS regression using the recalculated value of the dependent variable, a step which can be repeated as many times as may seem desirable.

Changes in Damage-Control Agent Productivity

In many cases, damage abatement functions are dynamic; in particular, there is a tendency for the efficacy of damage-control measures to decline over time. For example, bacteria populations typically develop resistance to antibiotics, necessitating the use of larger doses to achieve satisfactory control of infections. Dams and other flood control devices are subjected to water erosion, gradually weakening their ability to prevent floods and necessitating additional investment: in repair and renovation. Criminals tend to find ways of coping with each improvement in prevention technology making further improvements a continual necessity. In short, because damage abatement typically involves natural systems in which damaging agents tend to adapt to abatement efforts, declines in damage-control agent productivity tend to be the rule rather than the exception.

Producers, however, tend to exclude this factor from their production decisions. They do so, in part, because these declines in productivity are extremely difficult to anticipate so that there is generally very little reliable information on future trends available to incorporate into current production plans. In addition, these declines in productivity typically possess a very large public good component because they are caused by the combined actions of all producers (see, for instance, Regev, Shalit, and Gutierrez). As a result, individual producers perceive their own actions to have negligible effects on damage-control productivity and thus tend to operate within a myopic optimizing framework.[5]

Such environmentally induced changes in productivity have a different impact on the use of damage-control agents than do normal inputs. Consider what happens to demand for a normal factor of production when its productivity decreases because of some change in the productive environment. Decreased factor productivity means that total output will be less than it was previously for every level of input use. If the production function is a standard neoclassical one (specifically, if output is zero when use of any input is zero, if the marginal productivity of any factor is quite large at a zero level of utilization, and if marginal productivity is monotonically decreasing in factor use, i.e., the production function is concave), then this decline in factor productivity means that the marginal productivity of the factor will decrease at every level of factor use so that the level of utilization of that factor will also decline. In short, an environmentally induced decrease in productivity of a factor will decrease demand for it.

This line of argument was put forward for the case of pesticides by Carlson in his empirical study of the impact of resistance on pesticide use. Carlson argued that the development of resistance implied decreasing marginal pesticide productivity over time and, thus, that the demand should fall for pesticides to which resistance was developing. The standard characterization of this phenomenon, however, is that farmers' typical short-run response to the development of resistance to some pesticides is to increase usage levels as compensation for the decrease in pesticide productivity. Use of the affected pesticide decreases only when productivity is so low that alternative pesticides become more efficient. This pattern has been observed in every case in which resistance has eroded pesticide productivity over time. In fact, it is further borne out by the results of Carlson's study. In his investigation of pesticide demand, he found that resistance measures were positively correlated with demand for organophosphates (to which resistance had emerged only recently) while they were negatively correlated with demand for DDT--a chemical to which resistance was quite extensive.

Treating damage-control agents as normal inputs implies that farmers, medical practitioners, crime prevention experts, and others respond irrationally to environmentally induced changes in damage-control agent productivity. By contrast, analyzing damage-control agents in the context of an abatement function supports fully the rationality of their behavior in such situations. The optimality of increased damage-control agent usage is shown easily under short-run profit maximization using the model of damage abatement introduced above.

The types of changes discussed above have the effect of reducing the effectiveness of any given level of damage-control agent applied. Any given amount of damage-control agent will thus eliminate a smaller proportion of destructive capacity than before; in other words, more damage control agent is required to achieve any given reduction in destructive capacity.

To capture this effect, we redefine the abatement function, $G(\cdot)$, as a function of the amount of damage-control agent applied, X, and the level of resistance, R, where $G(X, R_1) \leq G(X, R_0)$ for $R_0 < R_1$ and for all X; in other words, $G_R \leq 0$ for all X. In fact, we will define R such that the strict inequality holds everywhere but at the minimal and maximal levels where increases in resistance may have no effect.

For ease of analysis, we will impose two additional restrictions. First, we will consider the effect of resistance only for the case of unimodal damage abatement functions which are the only ones used for empirical purposes. Second, we assume that the curves representing marginal effectiveness for two different levels of resistance cross only once; in essence, this assumption merely says that increased levels of resistance do not distort the shape of the marginal effectiveness function too much. Together, these imply that $G_{XR} > 0$--that increased resistance increases the marginal effectiveness of the damage-control agent--in the economic region. The reason for this is simple. For small values of X, increased resistance implies that marginal effectiveness must decrease. As shown in figure 2, only when $G_X(X_0, R_1) < G_X(X_0, R_0)$ will $G(X_0, R_1)$, the area under the new marginal effectiveness curve, be less than $G(X, R_0)$. Formally, $\int_0^{X_0} G_X(X, R_1)\, dX < \int_0^{X_0} G_X(X, R_0)\, dX$ implies that $G_{XR} < 0$ for small values of X. Since the two functions must both attain a value of 1 at the maximal dose level, however , G_{XR} must be positive for at least some X; the single crossing assumption ensures that this condition will not be reversed once it is attained.

The impact of increased resistance on damage-control agent demand can be analyzed formally via total differentiation of the first-order conditions given by (3), amended to include the shifter R in the abatement function. Rearrangement of the resulting equation yields

$$\frac{\partial X}{\partial R} = - \frac{\varepsilon_G}{G}\left[G_{XR} + \frac{G_X G_R}{G\varepsilon_G}\right]. \tag{19}$$

The expression on the right-hand side of (19) is positive whenever $G_{XR} > 0$; for the cases we are considering, the latter is true everywhere in the

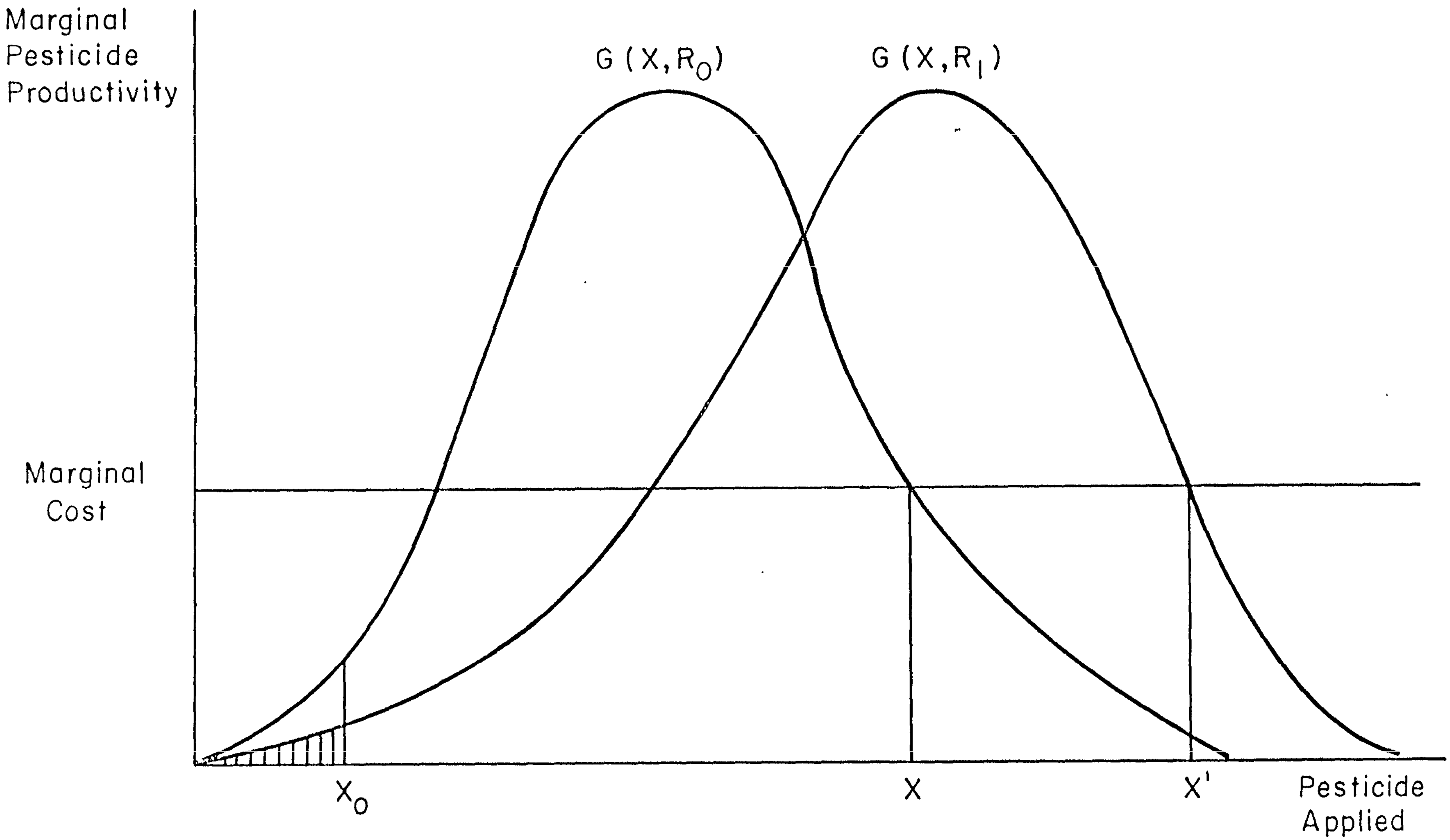

FIGURE 2, Impact of Increased Resistance on Marginal Pesticide Productivity

economic region and, thus, $\partial X/\partial R > 0$ for all the relevant application levels.

Why this is so can be seen easily in figure 2. The condition $G_{XR} > 0$ means that the economic region of the marginal effectiveness curve shifts to the right for all X's (as does the marginal value product curve) as shown by the change from $G(X_1 R_0)$ to $G(X_1 R_1)$. For any given level of marginal cost, the new level of demand, X', is then necessarily greater than the old level X.

Under the most commonly encountered conditions, then, an environmentally induced reduction in damage-control agent productivity has effects on a damage-control agent that are completely the opposite of the effect it would have on a normal input. Increased resistance increases marginal effectiveness and, hence, marginal productivity. The optimal profit-maximizing response, obviously, is to increase damage-control agent use precisely as has been observed in such situations.

Conclusions

This paper demonstrates the importance of incorporating correct specification of damage abatement processes in the estimation of production functions and input productivity. First, it shows that the use of traditional specifications (e.g., the Cobb-Douglas) leads to overestimation of the productivity of damage-control inputs and underestimation of the productivity of other inputs. When and if such estimates are used in policy determination, the resulting errors can be quite serious. In the case of pesticides, for instance, a policymaker guided by the econometric studies available would be led to encourage more extensive and intensive use of pesticides--at a time when pesticides were extremely overutilized.

The paper also shows that traditional specifications produce misleading predictions when damage-control agent productivity is changing over time. Traditional specifications suggest that the spread of resistance will lead to the reductions in the use of a damage-control agent. In contrast, the specification proposed here captures the phenomenon that actually occurs, namely, that the use of a damage-control agent will increase in response to resistance and that it will decrease only when resistance is so widespread that alternative measures are more cost effective.

Finally, the paper shows that a more sophisticated approach to damage abatement in production (like the one proposed here) can be incorporated into econometric work at little or no extra computational cost. Many of the distributions especially relevant in this context yield easily estimated damage-control agent demand relations from which most or all of the structural parameters can be recovered. The general availability of nonlinear estimation packages removes much, if not all, of the remaining difficulties associated with direct estimation of production. In sum, the specification of damage abatement proposed here adds considerable sophistication and accuracy to the analysis of the role of damage-control agents in production without making estimation any more difficult. It should thus prove to be quite useful for improving quantitative decision-making in all areas in which damage abatement is an important factor.

APPENDIX

Proof of the Upward Bias in Cobb-Douglas Estimates of Damage Control Agent Productivity

To investigate the impact of using the standard Cobb-Douglas form (10) in place of the true model given in (9), consider the standard Cobb-Douglas form as an approximation to the true model. Specifically, consider the Taylor series expansion of ln G(X) around $\bar{x}$, the mean value of ln X. Then, X becomes a function of x: $X(x) = e^x$ since $X = e^{\ln x}$; we thus have $\partial X/\partial x = \partial^2 X/\partial x^2 = e^x = x$.

The approximation is

$$\ln G(X) = \ln G(e^{\bar{x}}) + \eta_G(e^{\bar{x}})\ (x - \bar{x})$$

(A1)

$$+ \frac{1}{2} \cdot \frac{\eta_G(e^{\bar{x}})}{e^{\bar{x}}} [1 + \eta_g(e^{\bar{x}}) - \eta_G(e^{\bar{x}})]\ (x - \bar{x})^2 + \ldots$$

The approximated model is

(A2) $$q = \alpha + z\beta + \gamma \ln G(e^{\bar{x}}) + \gamma\eta_G(e^{\bar{x}})\ (x - \bar{x}) + v$$

where v, as we see from (11), is the sum of the higher order terms of the Taylor expansion and of the white-noise random variable u. The model given by (A2) is more conveniently written

(A3) $$q = \tilde{\alpha} + z\beta + x\tilde{\gamma} + v$$

where $\tilde{\alpha} = \alpha + \gamma[\ln G(e^{\bar{x}}) - \eta_G(e^{\bar{x}})\, x]$ and $\tilde{\gamma} = \gamma\, \eta_G(e^{\bar{x}})$. Since the error term v contains terms in $(x - \bar{x})^2$, $(x - \bar{x})^3$, and so on, which are undoubtedly correlated with x and may well be correlated with z, the OLS estimators $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\gamma}$ will give biased estimates of $\hat{\alpha}$, $\hat{\beta}$, and γ. Assuming, however, that the coefficients of these terms are suitably small, it is easy to show that the OLS estimators will be consistent for $\hat{\alpha}$, β, and $\hat{\gamma}$.[6]

Letting $y = [1\ z]$ and $\delta = \begin{bmatrix} \tilde{\alpha} \\ \beta \end{bmatrix}$, rewrite the model as

(A4) $$q = y\delta + x\gamma + v.$$

Let $M_x = I - x(x'x)^{-1} x'$ and $M_y = I - y(y'y)^{-1} y'$. Then the OLS estimators, $\hat{\delta}$ and $\hat{\gamma}$, are

(A5)
$$\hat{\delta} = \delta + \left[\frac{y'y}{n} - \left(\frac{y'x}{n}\right)\left(\frac{x'x}{n}\right)^{-1}\left(\frac{x'y}{n}\right)\right]^{-1}\left[\frac{y'v}{n} - \left(\frac{y'x}{n}\right)\left(\frac{x'x}{n}\right)^{-1}\left(\frac{x'v}{n}\right)\right]$$
$$\hat{\gamma} = \tilde{\gamma} + \left[\frac{x'x}{n} - \left(\frac{x'y}{n}\right)\left(\frac{y'y}{n}\right)^{-1}\left(\frac{y'x}{n}\right)\right]^{-1}\left[\frac{x'v}{n} - \left(\frac{x'y}{n}\right)\left(\frac{y'y}{n}\right)^{-1}\left(\frac{y'v}{n}\right)\right].$$

As long as $(x'x)/n$, $(y'y)/n$, and $(x'y)/n$ converge to finite numbers as the sample size gets large and as long as the coefficients of the terms in v are of order smaller than the sample size, the estimators $\hat{\delta}$ and $\hat{y}$ will converge to δ and $\tilde{\gamma}$, respectively, as the sample size gets large.

However, α and $\tilde{\gamma}$ are biased measures of α (the productivity of natural factors and omitted variables) and $\gamma\eta_G$ (the productivity of the damage control agent), respectively.

Consider first the case of $\tilde{\alpha}$. As we saw above,

(A6) $$\tilde{\alpha} = \alpha + \gamma\, [\ln G(e^{\bar{x}}) - \eta_G(e^{\bar{x}})\, \bar{x}].$$

The term in the square brackets is negative since $\ln G(e^{\bar{x}}) \leq 0$ and $\eta_G(e^{\bar{x}})$ $\bar{x} \geq 0$. As a result, $\tilde{\alpha} < \alpha$: The OLS estimator from the standard Cobb-Douglas specification underestimates the productivity of natural factors and omitted variables.

The bias in $\tilde{\gamma}$ is more subtle. The measure of marginal factor productivity generally derived from econometric studies is the marginal productivity of a factor evaluated at the mean levels of output and all the relevant inputs; this, for instance, is the measure used in the pesticide studies conducted by Headley; Campbell; and Carlson. For the case of the damage control agent X, this is

(A7) $$\widehat{\frac{\partial Q}{\partial X}} = \frac{\gamma \bar{Q} \eta_G(\bar{X})}{\bar{X}} .$$

The estimate derived from the standard specification is

(A8) $$\frac{\partial Q}{\partial X} = \frac{\widehat{\gamma \eta_G(e^{\bar{x}})} \bar{Q}}{\bar{X}} .$$

Now, $\ln X$ is a concave function of X; hence, by Jensen's inequality, $E \ln X <$ $\ln EX$, i.e., $\bar{x} < \ln \bar{X}$. Since e^X is monotonically increasing in X, $e^{\bar{x}} < e^{\ln \bar{X}} = \bar{X}$.

Next, consider the behavior of η_g in the economic region. It is straightforward to show that

(A9) $$\frac{\partial \eta_G}{\partial X} = \frac{\eta_G}{X} \left[1 + \eta_g - \eta_G \right] .$$

Since $\lambda \eta_g < -1$ because g(X) is a probability density and since $\eta_G > 0$ for the same reason, it is evident from (A9) that $\partial\eta_G/\partial X < 0$, i.e., $\eta_G(X)$ is monotonically decreasing in the range of economic use. This fact implies that $\eta_G(e^{\bar{x}}) > \eta_G(\bar{X})$ and, hence, that the estimate of marginal productivity derived from the standard specification is biased upward.

Moreover, as X gets larger, the rate of decrease of η_G increases and, therefore, the difference between $\eta_G(e^X)$ and $\eta_G(X)$ increases also. Since damage-control agents tend to be used at close to maximum effectiveness, i.e., X tends to be quite large, this bias will also tend to be quite substantial in practical examples.

FOOTNOTES

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[2]In many situations, G may be a function of state variables which are changing over time, that is, damage abatement may be dynamic as in the case of pesticide resistance discussed below. For reasons mentioned below, the decision-making framework is myopic and ignores these dynamic considerations.

[3]Note that G(0) may well be positive since natural factors, such as weather, natural predators, etc., may eliminate some of the pest's destructive capacity. As a result, output may be positive in the absence of damage-control-measures. This fact points up the difference between damage-control agents and directly productive inputs: Production may be impossible without a full set of the latter, but losses without damage control may well he limited to less than 100 percent of output. In fact, under many environmental conditions (low pest infestations and lack of vandals in an area), damage may be quite small under any level of damage-control agent use.

[4]Misspecification of the production relationship is only one of the potential sources of bias in this situation. Others include omission of pest population levels or other environmental factors (see, for instance, Carlson), the use of damage-control agent cost instead of the total cost of abatement, etc.

[5]When producers are able to take these productivity dynamics into account in their decisions, the relevant future impacts of current actions should be included in the analysis along the lines suggested by Regev, Shalit, and Gutierrez among others.

[6]Briefly the specific condition for the consistency of the OLS estimators is that the coefficients of the higher order terms of the Taylor expansion of ln G(X) be of an order of magnitude smaller than n, the number of observations in the sample.

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C. AN EMPIRICAL APPLICATION: THE PRODUCTIVITY OF INSECTICIDES IN COTTON PRODUCTION IN CALIFORNIA

This section presents an application of the framework presented in the proceeding section to data obtained from cotton growers in the Central Valley. We begin with a brief discussion of the data available and the relationships to be estimated. We then examine estimates of insecticide productivity parameters - one based on an exponential kill function associated with the insecticide use and the other based on a generic Cobb Douglas technology-obtained by direct estimation of the production function and by estimating the (first order) optimality condition determining pesticide use. The first specification performs better in the production function estimation; both seem to perform equally well in the estimates of the optimality condition. Finally, we examine the insecticide productivity parameters of the exponential kill function obtained by simultaneous estimation of the production function and the optimality condition.

Variables and Data

The empirical study used data obtained by a survey from 42 cotton farmers in the San Joaquin Valley of California. For a detailed description of the data set, see Farnsworth (1980). The variables used and their units of measurement are as follows:

Q = Output of cotton lint (pounds per acre)

Z_1 = Labor input (dollars per acre)

Z_2 = Fertilizer input (dollars per acre)

Z_3 = Machinery input (dollars per acre)

X = Insecticide (pounds per acre)

E_1 = Education (years of schooling)

E_2 = Experience (years of farming)

P = Output price (dollars per pound)

W = Insecticide price (dollars per pound)

D = IPM Dummy: D=1 if grower is using IPM.

D=0 otherwise.

The sample consisted of 42 cotton growers in the San Joaquin Valley. Pesticide use patterns at 26 of the farms were determined by independent pesticide consultants who tend to rely on Integration Pest Management (IPM) in setting their recommendations (Willey). The other 16 farms did not hire the independent consultants; their pesticide use patterns tended to be stem from the conventional Chemical Pest Management (CPM) approach, mostly advocated by sales personnel of a grochemical firms.

Empirical Model

Several assumptions were used to obtain the production function specification for the empirical application:

(1) The production function has constant returns to scale so that it suffices to consider the behavior of output per acre.

(2) The contribution to production of physical inputs other than pesticides follows the Cobb Douglas form.

(3) Education and Experience are exponential shifters of the production function.

(4) Output is proportional to damage abatement.

(5) Damage abatement is a result of an exponential kill function associated with pesticide use.

(6) The kill function parameter may be different for IPM and CPM.

These assumptions result in the following specifications

(1) $A = Ae^{c_1E_1c_2E_2}\ z_1^{a_1}z_2^{a_2}z_3^{a_3}\ 1-e^{-(g_1D_1+g_0(1-D))X)}$

where A is a scale parameter, c_1 and c_2 are the education and experience shifters, a_1, a_2, and a_3 are the output elasticities of labor, fertilizer and machinery and g_1 and g_0 are the exponentional kill parameters associated with insecticide use under IPM and CPM respectively. These kill parameters reflect the effectiveness of insecticides in damage control.

A more "generic" approach to modeling insecticide contribution to thee production process will treat it like any other physical output and result in the following specification:

(2) $Q = Ae^{c_1E_1+c_2E_2}\ z_1^{a_1}z_2^{a_2}z_3^{a_3}X^{Da_{41}+(1-D)a_{40}}$

where a_{41} and a_{40} are output elasticities of the insecticides under IPM and CPM respectively.

The first order optimality condition to determine insecticide use associated with the production function in (1) is

(3) $X = \ln\{1+\left[g_1D+g_0(1-D)\right]\ PQ/W\} / \left[g_1D+g_0(1-D)\right]$

and the optimality condition (s) is

(4) $X = \left[a_{41}D+a_{40}(1-D)\right]\ PQ/W$

Single Equation Production Function Estimates

Following the procedures introduced in the previous section we estimated two specification of the production functions corresponding to equations (1) and (2). Each specification was estimated under two assumptions: one was that insecticides have different impacts under IPM and CPM and the other was that insecticides have the same impact under IPM and CPM. The results of the estimation appear in Table 1.

The assumption that pesticides contribute to productivity in a Cobb Douglas way leads to output elasticities of pesticides that are not significantly different than zero and do not differ much between IPM and CPM. On the other hand, the assumption of exponential kill function leads to pesticides input parameters that are different than zero at the 95% level of statistical significance. Moreover, it suggests that pesticide effectiveness is vastly different under IPM and CPM. The insecticide kill parameter is more than 4 times bigger under IPM than CPM (1.31 vs .31). This suggests that 4 pounds of insecticides under CPM has the same marginal impact as 1 pound used with IPM and thus that adoption of IPM can lead to increased productivity and protection while reducing pesticide use.

The gains associated with the modeling of pesticides as a damage control agent operating through a kill function are obvious when one compares the R^2 of the different equation. The model based on equation (1) with different IPM and CPM parameters has an R^2 which is about 50% higher than the rest of the models[2].

Single Equation Estimation of the Optimality Condition

The optimality conditions (3) and (4) provide alternative means to estimate the insecticide productivity parameters of both production function specifications. Both were estimated under the two alternative assumptions regarding insecticide

Table 1: Production Function Estimates

Model	Generic input	Pesticides $(E_g(2))$	Expontential kill function $(E_g(1))$	
Parameter	IPM≠CPM	IPM=CPM	IPM≠CPM	IPM=CPM
Scale parameter h A	5.23* (8.7)	5.25 (9.03)	5.51 (9.9)	5.36 (9.45)
Education shifter C_1	.228 (1-6)	.224 (1.62)	.223 (1.676)	.231 (1.65)
Experience shifter C_2	.027 (.32)	.027 (.28)	.017 (.73)	.019 (.24)
Labor elasticity a_1	.10 (1.32)	.10 (1.35)	.10 (1.53)	.111 (1.49)
Fertilizer Elasticity a_2	.02 (1.3)	.02 (.88)	.02 (.741)	.032 (1.03)
Machinery Elasticity a_3	.04 (.75)	.05 (.81)	.03 (.50)	.04 (.5)
Insecticides Elasticity IPM a_{41}	.042 (.81)	.045 (.97)	NA	NA
Insecticides Elasticity CPM a_{40}	.049 (.96)	.045 (.97)	NA	NA
Insecticides kill parameter IPM g_1	NA	NA	1.31 (1.63)	1.14 (1.92)
Insecticides kill parameter CPM g_2	NA	NA	.31 (2.97)	1.14 (1.92)
R^2	.2198	.219	.307	.219

* The expressions in parenthesis are the t-statistics of the estimated parameter

productivity under IPM vs. CPM. The estimation results appear in Table 2.

All the estimates of the insecticide productivity parameters derived from the optimality conditions have positive values with very high degrees of statistical significance. Under both production function specifications, the insecticide productivity parameter is slightly larger when IPM is used, but one can not reject the hypothese that IPM and CPM have the same insecticide productivity parameters with higher degree of statistical significance.

The optimality conditions obtained under the two alternative production function specifications perform equally well in explaining variations in observed levels of insecticide use (and expenditures), since all the models presented in Table 2 have R^2 around .7. Thus, unlike the results shown in Table 1, the results shown in Table 2 do not demonstrate the superiority of either the kill function or the generic production function specification in modeling pesticides productivity.

Comparing the results of tables 1 and 2, note that the insecticide productivity parameters obtained from direct estimation of the production function are different from the ones obtained by estimation of the first order optimality conditions. This may be because growers do not pursue profit maximizing strategies in their pesticide decision making, so that the optimality conditions in (3) and (4) do not represent their behavior. If this is so, the results in Table 2 are not very useful. It is beyond the scope of this study to evaluate

TABLE 2: INSECTICIDE PRODUCTIVITY PARAMETERS DERIVED FROM OPTIMALITY CONDITION

Model Parameters	Generic Pesticide input		Exponential kill	
	IPM≠CPM	IPM=CPM	IPM≠CPM	IPM=CPM
Pesticide Elasticity IPM a_{41}	.033 (.808)	.032 (10.48)	NA	NA
Pesticide Elasticity CPM a_{40}	.031 (6.4)	.032 (2.4)	NA	NA
Pesticide kill Parameter IPM g_1	NA	NA	.32 (5.05)	.336 (8.6)
Pesticide kill Parameter CPM g_0	NA	NA	.34 (6.06)	.336 (8.6)
R^2	.726	.726	.729	.724

empirically the profit maximization hypothesis in the context of pesticide decision making; however, research that will derive and estimate conditions corresponding to behavioral modes other than profit maximization (e.g. expected utility maximization) seems very worthwhile. Another explanation for the divergence of the estimated parameters presented in Table 1 and Table 2 is more pedestrian but equally reasonable. Estimates are random variables and as such they assume values that are quite different than their means. This logic suggests that better utilization of both data and theory will occur when the production function and optimality conditions are estimated simultaneously.

Simultanous Equation Estimation of the Non-generic Specification

To obtain better estimates of the kill function parameters assuming profit maximizing behavior, we estimated equations (1) and (3) simultaneously using the nonlinear 3SLS procedure of Troll. The results of this procedure appear in Table 3. They suggest that the kill function parameter with IPM is substantially larger than of CPM; thus IPM utilizes insecticides more effectively. Specifically, 1 unit of insecticides applied under IPM has about the same effectiveness as 1.5 units of insecticides applied under CPM (since $g_1/g_0=1.5$). The model suggests that if a farmer applies 10 pounds of insecticides annually using CPM, he will obtain 92.2% of the potential yield (since .922 = 1-exp {10.2554 }). The same amount of output will be obtained by a farmer applying 6.98 pounds of insecticides using IPM (since 6.98=(10)(252)/(.365).

TABLE 3: SIMULTANEOUS EQUATION ESTIMATES OF THE PARAMETER OF THE EXPONENTIAL KILL FUNCTION SPECIFICATION

Parameter / Model	IPM≠CPM	IPM=CPM
Scale Parameter h A	3.45631 (3.35217)	3.12268 (3.0)
Education shifter c_1	.479616 (2.91809)	.52 (3.15)
Experience shifter c_2	.167125 (1.70)	.18 (1.86)
Labor elasticity a_1	.182 (2.12187)	.196 (2.18)
Fertilizer elasticity a_2	.10222 (2.70459)	.114 (3.08)
Machinery elasticity a_3	.074 (1.15)	.086 (1.33)
Insecticide kill parameter - IPM g_1	.356 (5.56)	.32 (7.2)
Insecticide kill parameter - CPM g_0	.255 (5.00)	.32 (7.2)

The results also suggest that an additional year of education has a much larger contribution to productivity than additional year of experience, and that labor and fertilizer have positive output elasticities which the output elasticity of machinery is not different than zero with high degree of statistical significance.

Conclusions

The empirical application reported here demonstrates the feasibility of estimation economic relationships derived from production function specifications that incorporate a biological kill function of pesticides. This specification was found to have more explanatory power than a generic Cobb Douglas specification in a equation estimation of cotton production function. When profit maximization is assumed, this new specification yield a simultaneous equation system that was estimated and demonstrated that insecticide effectiveness in cotton is almost 1.5 times higher if IPM rather than CPM is used.

Obviously, these are only exploratory results. Better and more-data were needed to better value the usefulness of the specifications suggested here. This study, however, serves as an encouraging first step.

Footnotes

[1]This paper was writtin by Erik Lichtenberg, Yacov Bur and David Zilberman.

[2]Moreover, the F-statistics of the models based on equation (1) with different coefficients for IPM and CPM is statistically different than zero with much higher level of significance than the F-levels of the other models.

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Farnsworth, R.L. "A Decision Theoritical Analysis of Alternative Pest Control Strategies: A Case Study of Cotton Growers in California" Ph.d Thesis, University of Californa, Berkeley, 1980.

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D. AVENUES OF FURTHER RESEARCH

The work presented in the preceding two sections suggests that the use of our econometric approach to estimating pesticide productivity is appealing on empirical as well as theoretrical grounds. Despite the shortcomings of the California cotton data, the results do indicate that our methodology can yield more accurate, believable estimates of pesticide productivity than the generic approach at no significant additional cost in terms of complexity or expense of computation. Thus, it appears that further work along would be well justified. It would be especially interesting to apply the methodology to more disaggregated data on the use of specific pesticides (or classes of pesticides) on a crop with the aims of distinguishing the productivities of specific pesticides and, possibly, patterns of substitutions among pesticides. (The latter task, clearly, would require extension of the model to a multidimensional case, i.e., some further methodological work.) During 1985, we conducted a brief investigation into potential data sources for such a endeavor. Two sources seemed particularly interesting:

(1) The USDA recently completed a rather thorough survey on pesticide use on corn and soybeans in the Midwest. This data set contains very detailed information on the amounts of each chemical used, other inputs, etc. and could thus be used to examine substitution patterns among pesticides. Its chief drawback is that no information on yields was collected, which makes it difficult to use for estimating productivity. Yield

estimates could be constructed, at the expense of some precision, of course; however, doing so would require a significant investment of time and effort.

(2) John Allison of the University of Georgia has collected data on pesticide use in Georgia pecan production which is quite complete. It would make an excellent data base for further empirical work. We have discussed using it with Professor Allison and believe we can get access to it, if funded to do so. From the EPA's perspective, the chief drawback to this data is the nature of the crop; since pecan production tends to be localized, the estimates obtained would have only limited national significance.

Other data sources we have heard of but have not investigated more thoroughly include information on pesticide use in apple production in Virginia collected at VPI and data on pesticide use on corn and soybeans in Illinois collected by Earl Swanson. In sum, there is adequate data available for research along these lines should EPA find it desirable to pursue it. It also seems that both the EPA and the USDA should have a common interest in this area of research, since pesticide productivity is of concern to both agencies. Thus, one possibility might be an effort sponsored jointly by these two agencies.

IV. THE ECONOMICS OF RE-ENTRY REGULATION

One of the most common measures used to protect farmworkers and other rural inhabitants from the health hazards posed by applied pesticides is to forbid entry into treated fields for a specified period of time during which pesticide residue levels (and hence health risks) are thought to be excessive. (Similar regulations aim to protecting consumers by forbidding harvest for a specified interval after application of pesticides.) Often, these re-entry regulations lead to reductions in growers' incomes by preventing optimal scheduling of harvest or of intraseasonal activities like pruning or irrigation and thereby causing decreases in yield, quality or price received for the crop. Thus, whether the decision maker is an agency charged with protecting farmworkers (like the EPA) or a farmer deciding whether to work in his/her own field, the determination of an appropriate re-entry interval hinges on the choice of a tradeoff between risks to human health and safety, on the one hand, and the economic losses induced by regulation on the other.

This paper develops a methodology for deriving the set of these tradeoffs implicit in alternative re-entry intervals. The paper begins with a model describing the impact of re-entry regulation on farmers' use of pesticides and on the value of the harvest. Interestingly, the imposition of re-entry regulation may make it optimal for farmers to switch to prophylactic treatment of pests, a practice which has been widely criticized as inefficient in the literature on pesticide use. The paper then develops a model of the risk of acute poisoning from exposure to pesticide residues under different re-entry intervals. Finally, the production and health risk models are combined to derive an overall grower revenue/health tradeoff curve for the apple production case.

While the specifics of the framework developed here apply to pesticide-related problems, its more fundamental elements apply to a broad variety of regulations aimed at enhancing health and safety by restricting proximity to hazards either in time or over space, such as problems relating to industrial safety, the location of hazardous industries, the size of dams for flood protection, etc. The implications of the analysis thus carry beyond the pesticide case.

A Model for Production Under Re-Entry Regulation

For the sake of simplicity, we will concentrate on the problem of re-entry regulations affecting an individual farmer's harvest of a pesticide crop (fruits, vegetables), the kind of crop to which this form of regulation is applied most often. Assume that these is a time t_0 representing the earliest date at which the crop can be harvested; prior to t_0, the crop will be immature and hence not harvestable. Assume also that after t_0, the value of the crop declines because of decreased quality or because of price decreases due to seasonal increases in aggregate production, so that the farmer's revenue is maximized by harvesting at t_0. Formally, this implies a revenue function R(t) such that $R(t_0)=\max\{R(t)\}$, and, letting subscripts denote derivatives, $R_t < 0$ and $R_{tt} \leq 0$ for $t > t_0$. Production costs will be assumed to be constant and will thus be ignored.

Now assume that a pest appears at a time t_a shortly prior to the optical harvest time t_0. If left untreated, the pest will damage a proportion of the crop which will then be unsalable. The larger the pest population is, the greater the level of damage will be. This damage can be avoided by treating the crop with a pesticide. To simplify matters, assume that only a single standard treatment is available at a negligible cost. If the farmer treats the crop immediately upon arrival of the pest, i.e. chooses a treatment time $t_s=t_a$, the pest will be effectively eradicated and damage will be essentially reduced to zero. If, on the other hand, the farmer treats the crop before the pest arrives $(t_s<t_a)$, the pesticide will decay; it effectiveness will be reduced by the time the pest arrives and the farmer will sustain some crop losses. The longer is the interval between treatment and the arrival of the pest, the greater will be the decay of the pesticide and the damage caused by the pest.

These characteristics can be represented formally by letting the proportion of the crop damaged by a pest population of size k be a function $g(k,t_a-t_s)$, where t_a-t_s represents the time elapsed between treatment and the arrival of the pest. The preceding discussion suggests that $g_k > 0$, $g_t > 0$ and $g(k,0)=0$. Pesticide decay curves are typically convex, so that one would expect $g_{tt} \geq 0$ as well.

If the farmer is a profit-maximizer, she/he will always find it optimal to adopt a reactive pest management strategy (that is, to treat the crop upon the arrival of the pest) whenever feasible, which implies an optimal choice of $t_s=t_a$ whenever

$T \leq t_0 - t_a$. If the re-entry period T is sufficiently long, however (specifically $T > t_0 - t_a$), following the reactive treatment plan may force the farmer to delay the harvest and thereby lose revenue. In this case the farmer faces a tradeoff between lost revenues from crop damage and lost revenues from harvesting delays. Under some conditions, it may become optimal for the farmer to treat in anticipation of a pest problem, that is, to adopt a prophylactic treatment strategy. This practice has been much maligned in the pest management literature; however, it will be efficient under certain conditions described at greater length below.

It should be clear in addition that the farmer will never treat any earlier than needed to be able to harvest at time t_0, i.e., that $t_s \geq t_0 - T$; treating any earlier than $t_0 - T$ would imply accepting greater damage in return for no gain in revenue and is thus less profitable than treating at $t_0 - T$.

Finally, it should be evident that the farmer will always harvest the crop as soon as possible, that is, at least as soon as the re-entry period has ended. if the re-entry constraint is non-binding, then the harvest time will be t_0. If the re-entry constraint is binding, then the harvest will occur T periods after the treatment time; normalized (without loss of generality) to fit the revenue curve R this can be written $t_s + T - t_0$.

The pesticide use patterns adopted and revenues earned by the farmer thus depend critically on whether or not the re-entry interval constitutes a binding constraint. If it does not, then a reactive treatment strategy is always optimal, $t_s = t_a$, the crop will be harvested at t_0 and revenue will be $R(t_0)=R^*$. If it does, the the farmer will face a tradeoff between crop damage and decreased revenue. The optimal pest management strategy will be determined by the choice of a treatment time t_s which maximizes realized revenue, given by:

(1) $[1 - g(k,t_a-t_s)]R(t_s+T-t_0)$

subject to the constraint:

(2) $t_0-T \leq t_s \leq t_a$.

Because the convexity of the pesticide decay function makes the damage function $g(k,t_a-t_s)$ convex, the realized revenue function (1) will be convex unless R( ) is quite strongly concave. Thus, the optimal treatment plan must be analyzed according to two cases.

<u>Case 1</u>: (1) convex. The most likely case is that realized revenue (1) will be convex, so that the optimal treatment time will be either the maximum or minimum possible time, that is, either t_a or t_0-T. In essence, of course, this constitutes a choice between reactive $(t_s=t_a)$ and prophylactic $(t_s=t_0-T)$ treatments. The farmer will choose the one which gives the greatest profit. If $t_s=t_a$, there will be no damage (g=0) but the farmer will have to wait until t_s+T-t_0 to harvest and will thus realize a revenue of $R(t_a+T-t_0)$. If $t_s=t_0-T$, there will be damage $g(k,t_a+T-t_0)$; the farmer will harvest at t_0 and thus realize a revenue $[1-g(k,t_a+T-t_0)]R^*$. If the difference between these two realized revenues,

(3) $(t_a+T-t_0)-[1-g(k,t_a+T-t_0)]R^*$

is positive, the farmer will adopt the reactive strategy and treat at t_a. If it is negative, the farmer will adopt the prophylactic strategy and treat at t_0-T. An increase in the size of the pest population k will increase V and thereby make the farmer more likely to adopt a reactive strategy. An increase in the re-entry interval T, though, will increase V only if the marginal increase in the proportion of the crop damaged by treating earlier (g_t) is less than the marginal increase in the proportion of revenue lost by treating later (R_t/R^*). Thus, if $g_t > R_t/R^*$, an increase in T will make the farmer more likely to adopt a prophylactic strategy. An increase in the interval between the arrival of the pest and the optimal harvest data, that is, in t_0-t_a, will, of course, have precisely the opposite effect of an increase in the re-entry interval T.

Case 2: (1) concave. If the revenue function R( ) is sufficiently concave to make realized revenue (1) concave, the profit-maximization problem will have an interior solution defined by:

(4) $g_t R + (1-g)R_t = 0$

with sufficiency assured by:

(5) $Q = g_{tt}R + (1-g)R_{tt} \leq 0$

which holds by assumption. It is readily apparent that an increase in the re-entry interval will lead the farmer to treat earlier ($dt_s/dT = -[R_t g_t + (1-g)R_{tt}]/Q < 0$), thereby accentuating the tendency toward prophylactic treatment. If, as one would expect, the increase in damage from treating earlier is greater for larger pest populations than for smaller ones (i.e., $g_{tk} \geq 0$), an increase in the pest population size will induce the farmer to treat later ($dt_s/dk = -[g_{tk}R-g_kR_t]/Q > 0$), thereby reducing the tendency toward prophylactic treatment. As before, an increase in t_0-t_a will have the opposite effect of a increase in T.

Pesticide Use in Apple Production

Consider the case of re-entry regulation of organophosphate insecticides used to protect apple crops from infestations of coddling moth larvae from moth flights shortly prior to harvest. The yield and quality of the apples is assumed to increase up until the maturity data t_0, which is the earliest date at which the crop may be harvested. After t_0, yield and quality will remain constant for a considerable length of time. However, the price the farmer receives for the crop will decline as time passes because the aggregate supply of apples will increase as producers in other regions harvest and market their crops. This price decline will continue until the price of apples for fresh consumption equals the price for processing uses, at which point the price will remain constant. An analysis of the intraseasonal trends in farm-level apple prices in the three major producing states (Washington, Michigan, California) indicated that this price decline is convex and could be represented well by an exponential curve. Thus, the price received by a grower harvesting a full crop at time $t \geq t_0$ is $R^*e^{-a(t-t_0)}$.

The threat posed by a late-season flights of coddling moth consist of an infestation of larvae in the fruit, i.e., of wormy apples. This threat can be alleviated by using organophosphates to kill the moths before they lay eggs. Standard doses of these pesticides are typically applied; without loss of generality, normalize this standard dose to unity. Pesticide decay rates are typically modeled as exponential curves, so that the proportion of the pest population killed by a treatment applied at t_s is $e^{-b(t_a-t_s)}$ and the proportion surviving is $1-e^{-b(t_a-t_s)}$. Assume that all infested fruit is unsalable and that the proportion of the crop damaged is proportional to survivorship. Letting k represent the proportion of the crop damaged by a moth population of standard size, the damage function $g(k,t_a-t_s)$ will be in this case $k[1-e^{-b(t_a-t_s)}]$

The realized revenue function (1) in this case will thus be:

(6) $V=R^*e^{-a(t_s+T-t_0)}\{1-k[1-e^{-b(t_a-t_s)}]\}$

which is obviously convex. The difference in profit between treating at t_a and treating at t_0 is thus

(7) $V=R^*e^{-a(t_a+T-t_0)}-R^*\{1-k[1-e^{-b(t_a+T-t_0)}]\}$.

which will be positive whenever

$k>[1-\exp\{-a(t_a+T-t_0)\}]/[1-\exp\{-b(t_a+T-t_0)\}]=k_c$ and negative whenever k k_c. The optimal treatment strategy is thus:

(8) $$t_s=\left\{\begin{array}{ll} t_a & k>k_c \\ t_0-t, & k>k_c \end{array}\right\}$$

The comparative static results from the general case clearly hold here as well. In addition, it is straightforward to show that the faster the price declines over the season, the more likely the farmer is to adopt a prophylactic strategy ($dV/da < 0$) and that the faster the pesticide decays, the more likely the farmer is to adopt a reactive strategy ($dV/db > 0$).

To provide a empirical mechanism for evaluating the impact of re-entry regulation of pre-harvest use of parathion on apples in the three main U.S. producing states (Washington, California, Michigan), the model was parameterized as follows. A regression analysis of weekly data on farm-level prices received in Washington, California and Michigan over the period 1971-1980 on a time trend and dummies to control for differences among years and states yielded an estimate of the revenue decay parameter a = 0.0024. According to Johannes Joost, California extension specialist on apples, the maximum price received in 1984 was about $300/ton. At an average yield of 10 tons/acre, this suggests a maximum revenue of $150,000 for a 50-acre block. the regression analysis suggested that price levels in Michigan and Washington were about 17% and 32% above that of California; however, because Michigan harvests about 4 weeks after California and Washington, 2 weeks, the maximum price in these states should be 9.8% and 28.2% higher than California, respectively, giving estimates of about $165,000 per 50-acre block in Michigan and $192,000 per 50-acre block in Washington. An estimate of the parathion decay parameter b = 0.07 was taken from Spear et al.'s (1975a) study of parathion decay in California citrus orchards: examination of parathion decay data on Washington apples (Staiff et al. (1975)) indicated that the decay patterns in the two cases were essentially identical. Conversations with farm advisors indicated that, if left untreated, a coddling moth infestation caused by a population of normal size would damage about 10% of the crop; thus, k was given a value of 0.10. Calculation of the damage threshhold for prophylactic spraying over the range of reasonable re-entry periods, k_c, resulted in values ranging from .035 to .062, all well below k; thus, it appears that reactive treatment will always be optimal. In fact, apple prices would have to fall at about 5% per week before prophlactic treatment would become desirable.

Residue Poisoning From Parathion Exposure Among Apple Harvesters

This section develops a model for calculating the probability of clinical illness in workers as a result of exposure to residues of parathion applied to apples at various locations. The overall scheme is as laid out by Popendorf and Leffingwell (1982). In essence, the pesticide is applied, a decay process takes place in which some of the parathion is converted to the oxygen analog, paraoxon, and exposure takes place days or weeks later when crews enter the field to harvest the crop. If clinical illness results it is due to a dermally absorbed dose of paraoxon. There is considerable information available to quantify the various exposure-related steps in this process but very limited data on the geographic or climatological effects on the decay process itself. Hence, various assumptions are made in order to allow risk calculations to be carried out and these will now be detailed.

The characterization of the residue decay process will be based on the work of Spear et.a1.(1975a) and Popendorf and Leffingwell (1978). In both cases a set of linear ordinary differential equations was fit to field data on the dislodgeable foliar residues of parathion and paraoxon on citrus foliage.

Data on other crops suggests a qualitatively similar decay pattern as will be discussed below. The form of the equations used by Popendorf and Leffingwell was:

$$(9)\quad \begin{aligned} dx/dt &= -a_1x \\ dy/dt &= -b_1y \\ dr/dt &= a_2x + b_2y - c_1r \end{aligned}$$

where the observable residue of parathion (ng/cm^2) is the sum of the "short-term" parathion, x, and the "long-term" parathion, y, and r is the paraoxon residue. Both the data of Popendorf and Leffingwell on California citrus and Staiff et.al. (1975) on Washington apples suggests that the long-term decay rate of parathion equals that of paraoxon in the absence of rainfall, i.e. $b_1 = c_1$. In addition, it is clear that almost all the paraoxon is produced within the first few days after application when the total residue of parathion are high, i.e. the paraoxon production term b_2y is generally negligible. Hence a simplified decay model is:

$$(10)\quad \begin{aligned} dx/dt &= -a_1x \\ dy/dt &= -b_1y \\ dr/dt &= a_2x - b_1r \end{aligned}$$

A further simplification occurs insofar as it has been shown that after the first few days the hazard to workers is almost totally determined by the paraoxon residue (Spear et al. (1975b). Hence, if we constrain the period of interest to the that following the first several days post-application, which is the practical case, then the y component of the residue is of no interest, except insofar as it may aid in the estimation of b_1, and the decay modeled further simplifies to:

(11) $dx/dt = -a_1 x$

$dr/dt = a_2 x - b_1 r$

The solution to this set of equations is:

(12) $x(t) = x_0 \exp(-a_1 t)$

$r(t) = (a_2 x_0 / a_1 b_2)[\exp(-b_1 t) - \exp(-a_1 t)]$

There are, then, four parameters required to solve for r(t), the paraoxon residue, $a_1, a_2, b_1,$ and the initial condition x_0, The first three parameters are weather dependent whereas the last depends on the application rates and the pre-existing levels of foliar dust of the trees. Regrettably there appears to be very meager published data on parathion residue levels on apples around the country. However, the Washington apple data (Staiff, et.al., 1975) suggest a decay pattern quite similar to that observed in California citrus. Nigg et al. (1978, 1980) have studied the effect of weather variables on the parathion decay process and has concluded that rainfall and leaf wetness from other sources are principal determinants of the rate of residue disappearance. Hence, climatological variability in this investigation will be handled by assuming that the decay parameters, a_1, a_2 and b_1, will be the same for all three regions but that the frequency of summer rainfall will diminish the expected residue of paraoxon in a discontinuous fashion.

After the initial period of paraoxon production the decay of both parathion and parzoxon is essentially first order with decay constant b_1. That is, we consider the period where $\exp(-a_1 t) << \exp(-b_1 t)$ and $r(t) = r_0 \exp(-b_1 t)$ where $r_0 = a_2 x_0 / a_1 + b_1$. As mentioned above, Nigg (1975) developed an expression relating the influence of rainfall, leaf wetness, temperature and solar radiation on parathion residues. He stated that rainfall is a more important relative predictor of paraoxon residues than of parathion although he did not present a quantitative relation in the case of paraoxon. We will assume that rainfall and time are the principal determinants of paraoxon residue and use Nigg's rainfall adjustment factor for parathion since e it should lead to conservative results, i.e. somewhat higher paraoxon residue predictions than may actually be the case. Under these assumptions the paraoxon residue at the entry time T is given by:

$$r(T) = r_0 \exp(-.291CR)\exp(-b_1 T)$$

where CR is the cumulative rainfall during the interval (O,T). A one inch rainfall leads to a diminution of the residue by 25% and a two inch rainfall a 44% decline. These predictions are more or less consistent with the data presented by Gunther et.al. (1977) who report reductions in paraoxon residues on the order of 3 to 5 for rainfall amounts over 2.5 inches and little decay for rainfall under one inch.

Estimates of the parameters a_1, a_2 and b_1 are available from Popendorf and Leffingwell (1978). Also, the initial condition x_0 was estimated from their data by regressing their parameter a_0 against the applied amount. The regression expression is:

$$x_0 = 1690(AIA)^{.3067} \quad ng/cm^2$$

and the values used for the other three parameters are $a_1 = 0.8$, $b_1 = 0.08$, $a_2 = 0.05$. Hence, for any application amount, entry time and cumulative rainfall amount the paraoxon residue can be determined. It is now possible to relate this residue to the dermal dose and then the predicted red cell cholinesterase depression.

Popendorf and Leffingwell (1982) relate the foliar residue to the dermal dose deposited on the worker by the expression $k_d r(t) t_e$ where D is in mg/kg, t_e is the exposure time and k_d an empirically determined constant. Their Table X gives observed k_d values for various crops and pesticides. For paraoxon on apples we will assume a k_d value of 9.0 as was observed in citrus crops. The exposure time will be assumed to be eight hours.

For a single organophosphate the relation proposed by Popendorf and Leffingwell between dermal dose and the fractional inhibition of RBC cholinesterase is given by:

$$RBCD = 1-\exp(-k_e D/LD_{50})$$

where, for paraoxon, the dermal LD_{50} is 1.0 and k_e is set equal to 6.0 midway in the reported range of 4.7 to 7.3. While it is reasonable to assume that the entire crew is exposed to the same residue environment, personal factors enter into the relationship between residue and dermal dose and between dermal dose and cholinesterase response. However, there is no data to allow the modeling of these effects so we will assume that all workers experience the same cholinesterase response and confine the variability across the population to the dose-response curve.

For present purposes the relation between cholinesterase depression and the development of clinical signs and symptoms is shown in Figure 1 Milby, (1985). They are approximations based on clinical experience and values reported in the medical literature. The probability of clinical illness relates to each of the members of the crew at the end of one eight-hour day and not to the situation where the RBC cholinessterase depression is the result of several exposure episodes extending over multiple days. In order to predict the number of cases of illnesses the probability from Figure 1 is used, together with the crew size, to form the parameter of a binomial distribution which then allows the calculation of the probability that 0, 1, 2, ..N workers will become ill.

Economics and Health Impacts of Re-Entry Regulation

The models presented in the two preceding sections can be used to evaluate the impact of re-entry regulations on apple growers' revenues and apple harvesters' safety. The analysis will be conducted under the assumptions that a flight of coddling moths arrives four days before the optimal harvest date t_0 (i.e., $t_0-t_a=4$), that parathion is applied at a rate of 2.0 pounds per acre AIA, and that, as is typical, the crop produced on a 50-acre block will be harvested in one day by a crew of 10. Losses in growers' revenues will be compared to the probability that at least one worker will develop mild symptoms of parathion poisoning for rainfall levels of 0, 1, and 2 inches during the re-entry period as a means of taking into account the differences in weather conditions encountered in the different regions under investigation: California receives virtually no rainfall during the harvest period, Washington receives 0-1 inch and Michigan receives 1-2 inches under normal conditions.

The results of these calculations are shown in Table 1. On the health side, it is immediately apparent that the re-entry times issued by EPA (24 hours after application) provide virtually no protection to farmworkers under California conditions and very limited protection under Washington or Michigan conditions: at best, there is a 40% chance that at least one worker will become mildly ill. California standards (14 days) provide much better protection. Interestingly, though, the chance that at least one worker will fall ill are still as high as 10%. The results also indicate more stringent re-entry regulation might well be warranted in Washington and Michigan, which have no standards other than the EPA's.

It is important to realize that this analysis deals with the incidence of mild, not severe, poisoning episodes; positive probabilities of severe symptoms showed up in our model only at parathion rates far above normal usage levels on apples. However, this result holds only when the unit of analysis is a single 50-acre block. When the entire apply industry is considered, it is certain that at least one worker will develop mild symptoms and there will be a non-negligible probability of severe poisoning incidents.

On the economic side, it is easily seen that even moderate re-entry regulation imposes non-negligible costs on growers in terms of lost revenue. A re-entry time of 5 days, for example, results in a loss of 0.2% of total revenue, equivalent to absolute amounts of $300 per 50-acre block in California, $385 in Washington and $330 in Michigan. According to the Washington

Agricultural Statistics, the total harvest labor cost for a 50-acre block ran about $425, not much greater than these losses. Longer re-entry times produce losses on the order of 1-2%; if profit margins amount to about 10%, then losses on this scale would constitute 10-20% of the farmers' net earnings, a not inconsiderable chunk.

The extent of the tradeoffs between farmworker safety and grower revenue arising from different re-entry periods can perhaps be grasped best by examining the marginal cost of risk reduction under different re-entry times and the minimum value of illness avoidance they imply. Calculations of these values based on averaged risk values for Washington and Michigan are presented in Table 2. The estimates of the marginal cost of risk reduction obtained seem for the most part quite reasonable, the sole exception being very lengthy re-entry periods in Michigan, where the risks are quite low and hence can be decreased very little. The figures for Michigan show decreasing returns throughout. Washington, interestingly, shows increasing returns for moderate re-entry intervals and decreasing returns only for re-entry periods of 10 days or more the marginal cost of risk reduction behaves rather erratically, suggesting that risk declines rather slowly at high (4-5 days) and low (10 days) levels and more quietly for moderate levels. With the exception of very long re-entry periods in Washington and Michigan, the estimates of illness avoidance are comparable to those obtained by Maureen Cropper in her study of sick time behavior among factory workers. This suggests that re-entry regulation is a not unreasonable mechanism for improving farmworker safety.

It should be noted that these results apply for a single farm. For the industry as a whole, the marginal cost of risk reduction and value of illness avoidance are likely to be even lower, since the risks will probably rise faster than growers' losses. Thus, the present analysis probably understates the attractiveness of re-entry regulation.

TABLE 1

IMPACT OF RE-ENTRY TIMES ON HEALTH RISKS AND GROWERS' REVENUES

Re-Entry Period	Probability of at Least One Poisoning with Rainfall of			Proportion of Revenue Lost
	0"	1"	2"	
0-4	.93	.72	.40	0
5	.84	.69	.26	.002
8	.69	.34	0	.010
10	.47	.10	0	.014
14	.10	0	0	.024

TABLE 2

COST/RISK TRADEOFFS IN RE-ENTRY REGULATION OF APPLES

Re-Entry Period	Marginal Cost of a 1% Reduction in Risk			Implicit Value of Poisoning Avoidance		
	California	Washington	Michigan	California	Washington	Michigan
4	$3,333	$6,400	$ 3,883	$3,584	$ 7,758	$ 6,933
5	$8,000	$6,144	$ 4,328	$9,524	$ 8,031	$ 9,111
8	$2,727	$3,340	$ 5,500	$3,952	$ 6,484	$ 32,353
10	$4,054	$8,170	$33,000	$8,626	$28,666	$660,000

Final Remarks

The preceding analysis was based on a number of simplifications regarding both the production process and the health hazards posed by organophosphate use and should thus be viewed as illustrative rather than as an accurate depiction.

On the production side, the most notable of these simplifications were:

(1) Application of the pesticide was assured to be costless. Incorporation of a treatment cost might introduce an additional option for the grower, that of not treating the crop, which would be considered explicitly in a more realistic analysis.

(2) The size and time of arrival of the pest population were assumed to be known. In reality, both are stochastic. These uncertainties might alter the farmer's optimal behavior. For example, under uncertainty it might become optimal with larger than average populations or later than normal arrival times to treat twice, once prophylactically and a second time reactively; under the opposite kinds of circumstances, it might become optimal not to treat with pesticides at all. A more realistic analysis would incorporate these considerations.

(3) Attention was paid only to the immediate pre-harvest period. A more realistic analysis would examine the impact of re-entry regulation on the intraseasonal use of organophosphates, including the tradeoffs the grower

faces between increased damage from pest infestations and reduced yields from suboptimal scheduling of production activities.

(4) Every piece of fruit infested by larvae was assured to be usable (or, equivalently, salable only for processing uses). In reality, problems arise only when inspection reveals that the proportion of infested fruit from an orchard exceeds an EPA standard, at which point the crop must be sorted and the bad apples called. A more realistic analysis would incorporate this damage threshold. This phenomenon also raises two points of interest for further research: (a) the interrelations between FDA regulation of produce quality and EPA regulation of pesticide use and (b) the role of inspection effort and enforcement of FDA regulations in pesticide use.

On the health side, the most notable simplifications were:

(1) Parathion application rates, harvest crew sizes and harvest time required were all assumed to be uniform across and within states. A more realistic analysis would consider variations in these factors, looking especially at their distribution in different areas.

(2) The decay rates of parathion and paraoxon were assumed to be constant. In reality, the dynamics of these substances are different for the first 1-3 days after application, a complication that must be taken into account in examining re-entry periods of one or two

days. Moreover, the longer term decay rates are influenced by environmental conditions, notably rainfall. This latter consideration suggests that re-entry periods could be shortened under some environmental conditions and lengthened under others (i.e., that re-entry regulation could be made state-dependent) with no increase in actual risk to farmworkers. If the savings to growers from such conditional regulation at least matched the cost of monitoring residue levels, society could be made better off by switching to it. This question, too, then, is an important one for future research.

V. PROPOSALS FOR FUTURE WORK

A. Introduction

The following is a proposal for work to be carried out under the "Framework/Case Study Design for a Risk-Benefit Analysis of Pesticides" cooperative agreement (CR811200) during 1986.

During 1985, we focused on three major areas: (1) developing a welfare framework incorporating regional heterogeneity and Federal farm policy for estimating the benefits of pesticide use: (2) measuring pesticide productivity; and (3) developing a framework for estimating the impacts of farmworker safety regulations. The first area was addressed by two empirical studies of the impact of regulation on agricultural markets, one focusing on the role of agricultural policy in five major crops and the other focusing on regional heterogeneity in thee U.S. cotton market. The conceptual framework for the former was delivered to EPA in the paper by Lichtenberg and Zilberman, "The Welfare Economics of Regulation in Revenue - Supported Industries"; this framework was used to construct a computer algorithum and interactive IBM PC compatible software also delivered to EPA. In addition, we developed a regionalized empirical model of the U.S. cotton industry for use in analyzing the regional welfare impacts of pesticide regulation. The second area was addressed by an application of the pesticide production function formulation previously developed (Lichtenberg and Zilberman "The Econometrics of Damage Control", American Journal of Agricultural Economics, May 1986) to data on cotton production in California. The third area was addressed by a study of the impact of re-entry regulation on apple growers' revenues in California, Washington and Michigan, the chief U.S. apple-growing regions.

During 1986, we propose to intensify our efforts relating to estimating the benefits of pesticide use and to direct them toward problems of immediate concern to EPA Thus, our work will be more issue-oriented and will require closer collaboration with EPA staff than in the past. Specifically, we propose to channel our efforts in two main directions. First, we propose to refine our previous work both conceptually and operationally and to make it directly usable by EPA. Second, we propose to address a set of issues relating more closely to the current activity of the EPA, specifically, assessing the benefits of the use of fungicides as a class on tree crops. In particular, we hope to contribute in this way to the effort to assess the benefits of pesticide use overall described in Al McGartland's paper on "The Use of Pesticides in U.S. Agriculture: A Comprehensive Analysis of Benefits and Costs".

The specific work envisioned for these two areas in described in greater detail in what follows.

B. A Unified Framework for Assessing the Welfare Impacts of Pesticide Regulation

As part of our work under this cooperative agreement, we have developed and applied two frameworks for assessing the welfare impacts of pesticide regulation. One which allows disaggregation of the regional effects of regulation and another which incorporates agricultural policy. During 1986 we propose to extend this work by (1) refining the framework for incorporating agricultural policy by including additional features of these policies, notably acreage set asides; and (2) combining both approaches into a single, unified framework for assessing the product market welfare impacts of pesticide regulation.

U.S. agricultural policy has two principal components: an income support provision (currently deficiency payments) and a supply control mechanism (currently acreage set asides). During 1985, we developed a welfare framework which incorporated price support programs. However, the welfare implications of supply control mechanisms have yet to be addressed in any practical fashion.

Supply control features such as set asides have proven extremely difficult to model because their effects on farmers' decisions, and hence supply, are quite complex. To be eligible for deficiency payments, farmers must comply with set aside requirements. Thus, they must decide whether or not to participate in the farm program at the same time that they choose how much to produce, so that the supply decision becomes, in effect, a simultaneous discrete/continuous choice problem whose optimal solution depends on factors like land quality and capital constraints as well as relative prices. Data on these factors are usually unobtainable, as are data on participation rates (especially at the state and local levels). Moreover, because of slippage set asides typically affect supply in a complex, non-proportional fashion since farmers idle lower quality land to satisfy set aside requirements, increase the intensity of input use, including pesticide use, etc.

During 1986, we will develop a practical method for incorporating set asides into estimates of the welfare impacts of pesticide regulation. We will then revise the framework presented in "The Welfare Economics of Regulation in Revenue - Supported Industries" to include set asides and update the accompanying interactive software package for calculating these welfare effects accordingly.

Once this work has been accomplished, we will combine it with our method for regional disaggregation to create a unified framework for assessing the welfare impacts of pesticide regulation. This will be done in the context of an empirical model of the U.S. cotton market. Specifically, we propose to estimate (1) supply functions for the major U.S. cotton producing regions which take into account price supports, set asides and other relevant agricultural policies in an appropriate manner and (2) the welfare impacts of pesticide regulations. This work will then be used to develop interactive IBM PC compatible software which will permit EPA to estimate the welfare effects of proposed regulations affecting pesticide use on cotton.

C. A Comprehensive Analysis of the Benefits and costs of Fungicide Use in U.S. Agriculture.

The aim of EPA's regulation of pesticides under the Federal Insecticide, Fungicide and Rodenticide Act is to prevent and/or curtail excessive risks of adverse effects on human health and environmental quality from pesticide use. In many cases, this aim cannot be furthered appreciably through the chemical-by-chemical review process currently used by EPA; all too often, cancellation of one pesticide's registration means only that other, no less detrimental, chemicals are substituted for the canceled substance, with the net result that risks fall only slightly, if at all, while costs of production can be expected to rise. In such cases, the narrowness of scope of the regulatory review produces a policy that is undesirable from any vantage point.

An alternative approach would involve a comprehensive review of chemicals on the basis of function, e.g., herbicides on corn/soybeans, fungicides on tree crops, insecticides on cotton, etc. As McGartland has argued recently, such an approach may well make it possible to reduce overall pesticide use significantly and thereby make notable improvements in environmental protection.

One class of pesticides of particular interest is that of fungicides, especially those used on tree crops. Fungicides tend to be quite toxic and hence to pose substantial risks to the health of applicators, fieldworkers and so on. In addition, there is increasing evidence environmental contamination with these chemicals is much broader than had been supposed. Finally, the study of fungicides is quite timely, since several major chemicals in this class (captan, etc.) are scheduled for review in the near future.

Regulating this class of chemicals also poses some difficult conceptual problems for policymakers. A substantial proportion of fungicide use is directed at enhancing product quality rather than increasing the quality of output harvested, so that the benefits of fungicide use consist to a large extent of the value consumers place on such features as fewer blemishes, fewer insects or insect parts in fruit or vegetables, etc. which are not readily observable. This situation is complicated by the fact that marketing boards often use these indicators of product quality as a means of rationing the quantities of produce entering the market for fresh produce, that is, as a means of raising the average revenue received by growers in the industry. Thus, a certain proportion of the benefits of fungicide use represent growers' gains from the revenue-support mechanisms of marketing orders rather than the social willingness to pay for enhanced quality and estimates of those benefits must therefore be adjusted to reflect that fact (for a general approach, see Lichtenberg and Zilberman, "The Welfare Economics of Regulation in a Revenue-Supported Industry").

In its initial stages, then, this project will require two parallel, but complementary efforts. On the conceptual side we will identify the elements of product quality consumers are willing to pay for, investigate further the use of product quality indicators as rationing devices under marketing orders and, on the basis of these two strands, build a conceptual framework for examining the welfare impacts of reductions in fungicide use. On the empirical side, we will investigate actual uses of fungicides in terms of the major strategies in use, the range of alternatives available, methods of application, advantages and disadvantages, likely substitution patterns under alternative forms of regulation (especially across-the-board cutbacks on all fungicides applied), yield and quality effects, etc. We will then continue the conceptual and empirical investigations of the first stage in an empirical study of the welfare impacts of reductions in fungicide use on a crop of national importance; possibilities in this regard include apples, oranges and grapes.

It should be noted that, because of its direct policy relevance, this project will require very close cooperation with EPA. We thus expect to be carrying on much more frequent consultation with EPA than we have in the past.

D. Economic Analyses of Special Review Chemicals for the Office of Pesticide Programs

Economic analyses pertaining to the regulation of pesticides are utilized by the Administrator of EPA for various purposes, primarily to comply with the requirements of the Federal Insecticide, Fungicide and Rodenticide Act (FIFRA) and Executive

Order 12291. Under both FIFRA and E.O. 12291, analyses are needed for review of existing regulations, or development of rulemaking, policies, guidance and statutory amendments for pesticide regulatory programs. Under FIFRA, the Administrator is required to consider risks and benefits when making registration decisions on a pesticide. In order to assess the benefits, data on the impacts of alternative regulatory actions on specific pesticides are needed.

These same analyses are of interest to the members of the Western Consortium for use in their own state regulatory agencies and other needs. Further, state universities and agencies are prime sources of information on which analyses are based. It is of mutual benefit for EPA and the Western Consortium to cooperate in the development of analyses related to pesticide policies, strategies, legislation, rules and regulation of specific chemicals.

Accordingly, it will be required under this agreement that economic analyses of joint interest be conducted, as specified by the EPA Project Officer and Western Consortium Project Manager. This will include analyses of actions on specific problem pesticides (Special Reviews) as well as analyses of regulations, rulemaking policies, strategies and guidance.

Analyses of regulation and policies may address many issues including direct economic cost effects and changes in welfare. Analyses generally consider effects on production costs, commodity pricing, and distributional effects as well as societal gains and losses. Analyses of Special Review Chemicals typically will concentrate on use sites in the Western US. region. Typically, economic impacts of shifting from use of a Special Review Chemical to other chemicals or non-chemical alternatives (including integrated pest management/biological controls) are the focus of such analyses. To the extent possible, analyses of rules, regulations, policies, etc., consider individual producer unit effects as well as net welfare changes from the proposed regulation.

Analyses may be undertaken independently by the Western Consortium or in cooperation with teams of experts (e.g. universities, pesticide user groups). Also, in order to perform the analyses, considerable information gathering will be necessary. Accordingly, the Western Consortium will undertake such travel and incur other expenses including those relating to the organization and coordination of meetings and symposia, obtaining peer review and other information gathering activities, as may be required. The results of such efforts will be incorporated into the appropriate analyses.

E. Other Projects

In addition to the two main efforts described above, we will continue to study the possibilities for applying our approach to econometric estimation of pesticide productivity (Lichtenberg and Zilberman, "The Econometrics of Damage Control", AJAE, May 1986) to USDA data on pesticide use in U.S. agriculture or to data on pesticide use in Georgia pecan production.

F. Deliverables

The outcomes of the studies undertaken will be presented to EPA in the form of a final report, to be delivered at the end of the budget period. In addition, we will deliver IBM PC compatible software allowing EPA to calculate the welfare effects of pesticide regulation on the cotton market as described in Section II.