Another Look at Pesticide Productivity and Pest Damage

Since the contribution of Lichtenberg and Zilberman (1986), the econometric specification of production systems that involve damage-control inputs has been widely debated. By and large, within agricultural economics, this debate has centered on the proper specification of the production role that pesticides play. Even the most casual reading of this literature highlights two salient characteristics. First, the debate focuses almost exclusively on the representation of damage-control inputs in single-output, plant-based production systems. And, second, the primary emphasis is on properly measuring pest damage to planned (maximal) output and the marginal productivity of pesticides.

The interest in the marginal productivity of pesticides is easy to understand. Economic efficiency dictates that the marginal social benefit from applying pesticides be equated to marginal social cost. The marginal productivity of pesticides is an important component of marginal social benefit.

It seems equally obvious why economists should be interested in measuring pest damage to output. Certainly, proper modelling of the economic damage caused by pests requires proper modelling of output damage. But output damage, considered alone, does not measure accurately the producer's private cost of pests.

Output damage, as traditionally defined, instead measures pest damage to maximal potential output realized from a given bundle of inputs. A more appropriate economic measure of the producer's private cost of pests is the producer's profit (quasi rent) loss due to pests. Conventional damage measures are an important component of this private cost, but they do not fully capture it. In fact, as we show, that *for rational profit maximizers conventional output damage measures systematically misstate the revenue and profit losses associated with the presence of pests*.

The cause of the divergence between the traditional pest-damage measure and the producer's private cost of pests is easy to trace. The former does not capture the economic adjustments to input use and production practices that rational economic decisionmakers make when using damage-control inputs. It simply measures physical damage to planned output, holding all inputs fixed, that actual pest infestations incur. The latter measure, on the other hand, accounts for rational actions taken to ameliorate pest damage, and thus captures the actual economic losses to farmers.

The implications of a possible divergence between traditional pest-damage measures and the actual economic loss due to pests are potentially important on a number of levels. First, and most simply, it is important in and of itself in empirical economics to get the numbers right. Second, and perhaps more importantly, the social costs and benefits of damage-control inputs are important matters of public concern. Many damage-control agents, such as pesticides, are often thought to have social costs (or benefits) that diverge from the private costs (or benefits) of individuals making decisions about their level of application. Thus, they have become a natural target for public regulation. Informed public regulation requires an accurate accounting of private, as well as social, costs and benefits. If the traditional measure of pest damage does not capture the producer's private cost of pests, sound policy making requires, at a minimum, that it be adjusted so that it does.

Following Lichtenberg and Zilberman (1986), Chambers and Lichtenberg (1994), and Fox and Weersink (1995), this paper develops a method for measuring quasi-rent losses due to pests and implements the method empirically using a panel-data set for Greek olive production. Our method has a number of important by-products, which merit independent study on their own. It yields both a measure of the marginal productivity of pesticides and pest damage to planned (maximal) output. The latter is the conventional damage measure considered in the literature. But because the method also provides a measure of the economic damage associated with the presence of pests, that economic damage is decomposable into its component parts, one of which includes damage to planned output. In addition, our method allows one to determine how pesticide application biases the optimal use of other variable inputs, how it affects the structure of quasi rents collected by quasi-fixed factors of production, and the general optimal supply-response characteristics of a farmer confronting pests.

In what follows, we first develop the basic production model. The damage specification follows the path-breaking work of Lichtenberg and Zilberman (1986), as extended by Fox and Weersink (1995) to allow for the potential presence of increasing marginal returns to the damage-control agent. The basic production model is then incorporated into a short-run supply response framework based on rational producer behavior. Here, we follow Chambers and Lichtenberg (1994) and develop a dual representation of the supply-response system associated with the Lichtenberg-Zilberman-Fox-Weersink specification of the damage-control technology.

A dual representation of the supply-response system is used because it facilitates measurement of the economically rational response producers make in the presence of pests. A primal representation, which is often used to obtain traditional damage measures, retards accurate measurement of such effects. And practical measurement from a primal system is only available after the inversion of first-order conditions associated with optimal behavior. This inversion process, because of its numerical nature, necessarily introduces yet another form of approximation error. The guiding principle is simple. The producer's profit loss is the appropriate measure of the economic loss due to pests. Therefore, we model the focus of our interest directly rather than indirectly as a primal approach would require.

After the representation is developed, we then show how to decompose the economic damage associated with the presence of pests, how to measure the shadow prices of damage-control agents, how to measure how pesticide application biases variable input use, and how pesticide application affects the relative returns to quasi-fixed factors of production. An econometric specification of our theoretical model follows, and that econometric specification is fit using a panel data set on Greek olive producers. The empirical results are then presented and thoroughly discussed, and the paper concludes.

1 The Basic Model

For a given level of initial pest incidence, the farm production technology in period t for a farmer with farm-specific characteristics, s, is represented by the closed, nonempty, production possibilities set

$$T(t,s) = \{(x,k,z,y,b^r) : (x,k,z) \text{ can produce } y \text{ for a given level of } (b^r,s,t)\}$$

where $x \in \mathbb{R}^N_+$ is a vector of variable inputs, $k \in \mathbb{R}^K_+$ is a vector of quasi-fixed inputs, y is output,[1] b^r represents the level of pest infestation (more generally, damage-agent incidence), and $z \in \mathbb{R}^Z_+$ is a vector of damage-control agents.

Following Lichtenberg and Zilberman (1986), Fox and Weersink (1994), Saha, Shumway, and Havenner (1997), and an extensive biological literature,[2] our specification of the technology simultaneously recognizes the asymmetric role that damage-control agents play in the production technology while permitting them to

[1] Our empirical application is for a single-product tree crop, olives. Therefore, to avoid excessive notation, we develop the model for a scalar output technology. The extension to a multi-output production system is straightforward and largely notational.

[2] Some studies, for example, Carpentier and Weaver (1997) while recognizing the validity of the asymmetric specification for field-trial type data question its use for data drawn from farm-level observations.

exhibit increasing marginal returns, thus,

$$T(t,s) = \{(x,k,z,y,b^r) : y \leq g(b^r,z,k,t,s)\, f(x,k,t,s)\},$$

where $f(x,k,t,s)$ represents maximal output obtainable from variable and quasi-fixed input use, and $g(b^r,z,k,t,s)$, whose range is restricted to lie in $[0,1]$, represents the percentage of maximal output realized in the presence of pest infestation, b^r, with application of damage-control agents at z. Thus, $1-g(b^r,z,k,t,s)$, which represents percentage of output lost in the presence of pests, is the traditional measure of pest damage.

Because our empirical application is to a tree crop and our capital measures include both land and capital equipment, we assume that the long-run maximal output technology exhibits constant returns to scale in x and k, and thus

$$f(\mu x,\mu k,t,s) = \mu f(x,k,t,s) \qquad \mu > 0.$$

As will become apparent, our specification allows the technology to exhibit either increasing or decreasing marginal returns in the damage-control agents, z, so that this assumption does not imply that $T(t,s)$ exhibits either constant or nonconstant returns to scale.

The primary focus in the empirical literature on damage control has been on the estimation of both components of actual production, maximal or planned production, $f(x,k,t,s)$, and damage to planned production, $1-g(b^r,z,k,t,s)$. A major theme of this paper is that the value of damage to planned production does not accurately measure either the actual revenue loss farmers suffer in the presence of pests or their lost profit due to the presence of pests. To demonstrate these points, we need an economic model of farmer's gains and losses in the presence of pests. That model is provided by a restricted-profit function which measures the quasi rents that a farmer collects from his or her quasi-fixed input endowment.

To develop the restricted-profit function for this technology, it is first convenient to develop the restricted-profit function that would prevail in the absence of any pests. That profit function gives the *maximum maximorum* quasi rent obtainable from a fixed input endowment. For a farmer facing output price $p \in \mathbb{R}_{++}$ and variable input prices $w \in \mathbb{R}^N_{++}$, the maximal quasi rent from farming with a quasi-fixed input endowment of k is that obtained in the absence of a pest infestation when $g = 1$:

$$\begin{aligned}
\pi(p,w,k,t,s) &= \max_{x,y}\{py - w'x : y \leq f(x,k,t,s)\} \\
&= \max_{x}\{pf(x,k,t,s) - w'x\} \\
&= \max_{f}\left\{pf - \min_{x}\{w'x : f = f(x,k,t,s)\}\right\} \\
&= \max_{f}\{pf - c(w,f,k,t,s)\}.
\end{aligned}$$

$\pi(p,w,k,t,s)$ is a restricted-profit function defined in terms of the quasi-fixed factors, and $c(w,f,k,t,s)$ is the minimal variable cost associated with production *in the absence of any pesticide damage*.

By standard results (Chambers, 1988), $\pi(p,w,k,t,s)$ is sublinear (positively linearly homogeneous and convex) in (p,w), nondecreasing in p, nonincreasing in w. It also satisfies Hotelling's Lemma. Because $f(x,k,t,s)$ exhibits constant returns to scale, $\pi(p,w,k,t,s)$ is also positively linearly homogeneous in the endowment of quasi-fixed factors of production

$$\pi(p,w,\mu k,t,s) = \mu\pi(p,w,k,t,s) \qquad \mu > 0.$$

Thus, if the technology is smooth, the Clark-Wicksteed product exhaustion theorem applies and the quasi-rent to the fixed input endowment can be decomposed into returns to each of the quasi-fixed factors of production as

$$\pi(p, w, k, t, s) = \pi_k(p, w, k, t, s)' k, \tag{1}$$

where $\pi_k(p, w, k, t, s) \in \mathbb{R}^K$ denotes the gradient of π in k. In words, each element of $\pi_k(p, w, k, t, s)$ defines a shadow price for the relevant quasi-fixed factor and the inner product of the shadow-price vector and the vector of fixed factors completely exhausts quasi-rent. The product of a quasi-fixed factor's shadow price and its level has the natural interpretation as that quasi-fixed factor's quasi rent.

The separable nature of the asymmetric damage specification inherent in $T(t, s)$ makes it relatively easy to go from maximal quasi-rent to quasi-rent that will be realized in the presence of pests. From the specification of $T(t, s)$, the quasi-rent from farming obtained in the presence of a pest infestation, b^r, and damage-control agent usage of z is

$$\begin{aligned} \Pi(p, w, k, b^r, z, t, s) &= \max_{x,y} \{py - w'x : y \leq g(b^r, z, k, t, s) f(x, k, t, s)\} \\ &= \max_{x} \{pg(b^r, z, k, t, s) f(x, k, t, s) - w'x\} \\ &= \pi(pg(b^r, z, k, t, s), w, k, t, s) \end{aligned}$$

The trick in moving from the first line of the definition to the second (and then the third) is to recognize that when there is no pest damage, the farmer's revenue is $pf(x, k, t, s)$. In short, the farmer collects all of the revenue associated with planned or maximal output. When there is pest damage, however, the farmer only collects $pg(b^r, z, k, t, s) f(x, k, t, s)$ where $g(b^r, z, k, t, s) \leq 1$, so that $pg(b^r, z, k, t, s) \leq p$. Thus, the damage to planned output, in economic terms, takes the exact same form as a reduction in the effective output price to farmers from p to $pg(b^r, z, k, t, s)$. This permits incorporating damage into quasi rent via the output price term in the restricted-profit function that would prevail in the absence of pests.

If there exist unique quasi-rent maximizing input demands, $x(p, w, k, b^r, z, t, s)$, and supply, $y(p, w, k, b^r, z, t, s)$, then by Hotelling's Lemma, $\Pi(p, w, k, b^r, z, t, s)$ is differentiable in (w, p) and

$$\begin{aligned} x(p, w, k, b^r, z, t, s) &= -\Pi_w(p, w, k, b^r, z, t, s) \\ &= -\pi_w(pg(b^r, z, k, t, s), w, k, t, s), \end{aligned}$$

and

$$\begin{aligned} y(p, w, k, b^r, z, t, s) &= \Pi_p(p, w, k, b^r, z, t, s) \\ &= \pi_1(pg(b^r, z, k, t, s), w, k, t, s) g(b^r, z, k, t, s), \end{aligned}$$

where $\Pi_w \in \mathbb{R}^N_-$ denotes the gradient of Π in w, Π_p the partial derivative of Π in p, and π_1 the partial derivative of π with respect to its first argument. Thus, $\pi_1(pg(b^r, z, k, t, s), w, k, t, s)$ represents the *optimally chosen maximal potential output associated with a pest infestation of* b^r and pesticides applied at level z, and optimal supply, $y(p, w, k, b^r, z, t, s)$, is the product of that maximal potential output and $g(b^r, z, k, t, s)$.

2 Measuring Pest Damage, Marginal Returns to Damage-Control Agents, and Damage-Control Biases

2.1 Measuring Economic Loss due to Pests[3]

In the absence of pests, $b^r = 0$, a farmer with a quasi-fixed factor endowment of k who applies no damage-control agents realizes a quasi-rent of

$$\Pi(p, w, k, 0, 0, t, s) = \pi(p, w, k, t, s).$$

In the presence of a pest infestation at b^r a farmer who applies damage-control agents at level z realizes quasi-rents equalling:

$$\Pi(p, w, k, b^r, z, t, s) = \pi(pg(b^r, z, k, t, s), w, k, t, s),$$

which, so long as $g(b^r, z, k, t, s) > 0$, can be rewritten as

$$\begin{aligned}
\Pi(p, w, k, b^r, z, t, s) &= \pi(pg(b^r, z, k, t, s), w, k, t, s) \\
&= pg(b^r, z, k, t, s)\,\pi_1(pg(b^r, z, k, t, s), w, k, t, s) + w'\pi_w(pg(b^r, z, k, t, s), w, k, t, s) \\
&= py(p, w, k, b^r, z, t, s) - c\left(w, \frac{y(p, w, k, b^r, z, t, s)}{g(b^r, z, k, t, s)}, k, t, s\right).
\end{aligned}$$

The quasi-rent loss associated with a pest infestation of b^r if the farmer applies damage-control agents at z is thus the difference between maximal possible quasi-rent and quasi-rent realized in the presence of pests. In terms of symbols that becomes.

$$\begin{aligned}
Q(p, w, k, b^r, z, t, s) &= \Pi(p, w, k, 0, 0, t, s) - \Pi(p, w, k, b^r, z, t, s) \\
&= \pi(p, w, k, t, s) - \pi(pg(b^r, z, k, t, s), w, k, t, s) \\
&\geq 0,
\end{aligned}$$

or in percentage terms

$$q(p, w, k, b^r, z, t, s) = 1 - \frac{\pi(pg(b^r, z, k, t, s), w, k, t, s)}{\pi(p, w, k, t, s)}.$$

A complete measure of the economic damage that the farmer suffers from the presence of the pest is obtained by adding the cost of applying the damage-control agent to $Q(p, w, k, b^r, z, t, s)$. Given $Q(p, w, k, b^r, z, t, s)$, however, total economic damage is trivially calculated. Hence, our focus in what follows is exclusively on $Q(p, w, k, b^r, z, t, s)$ and $q(p, w, k, b^r, z, t, s)$

Pest damage studies have concentrated on $1 - g(b^r, z, k, t, s)$, which measures *physical damage to the planned level of production.* $Q(p, w, k, b^r, z, t, s)$, on the other hand, takes account of both optimal supply and variable-input adjustments that are induced by the presence of the pest. A simple decomposition of $Q(p, w, k, b^r, z, t, s)$ illustrates:

$$Q(p, w, k, b^r, z, t, s) = R(p, w, k, b^r, z, t, s) - C(p, w, k, b^r, z, t, s),$$

where

$$\begin{aligned}
(2) \qquad R(p, w, k, b^r, z, t, s) &= p\left[y(p, w, k, 0, 0, t, s) - y(p, w, k, b^r, z, t, s)\right] \\
&= p\left[\pi_1(p, w, k, t, s) - g(b^r, z, k, t, s)\,\pi_1(pg(b^r, z, k, t, s), w, k, t, s)\right],
\end{aligned}$$

[3] This section differs markedly from the initial version of the paper. A particularly thoughtful comment by a reviewer spurred the additional theoretical analysis that led to those changes. We would like to thank him or her for the contribution.

and

$$(3)\qquad \begin{aligned} C(p,w,k,b^r,z,t,s) &= w'\left[x(p,w,k,0,0,t,s)-x(p,w,k,b^r,z,t,s)\right] \\ &= w'\left[\pi_w\left(pg\left(b^r,z,k,t,s\right),w,k,t,s\right)-\pi_w\left(p,w,k,t,s\right)\right]. \end{aligned}$$

$R(p,w,k,b^r,z,t,s)$ measures the revenue loss due to the presence of pests. Thus, it can be thought of as the *revenue (supply) effect.* $C(p,w,k,b^r,z,t,s)$ measures the difference in optimal variable cost associated with the absence and presence of pest. It can be thought of as the *cost (variable input) effect.*

$g(b^r,z,k,t,s)$ is a clearly a component of $R(p,w,k,b^r,z,t,s)$. But $g(b^r,z,k,t,s)$, which measures the direct damage done by pests to output, ignores components of the revenue effect and all of the cost effect in $Q(p,w,k,b^r,z,t,s)$.

2.1.1 Comparing Damage Measures

There are at least three natural measures of pest damage. The first is the traditional measure, $1-g(b^r,z,k,t,s)$, which measures physical damage to potential maximal output. A second is $R(p,w,k,b^r,z,t,s)$, which measures the revenue loss due to pests. And the third is $Q(p,w,k,b^r,z,t,s)$. We now compare these three measures.

The difference between maximal potential output in the absence of pests and output realized in the presence of pests is the revenue effect divided by the price of output:

$$\begin{aligned} \frac{R(p,w,k,b^r,z,t,s)}{p} &= y(p,w,k,0,0,t,s)-y(p,w,k,b^r,z,t,s) \\ &= \pi_1(p,w,k,t,s)-g(b^r,z,k,t,s)\,\pi_1\left(pg\left(b^r,z,k,t,s\right),w,k,t,s\right). \end{aligned}$$

The traditional measure of output loss equals maximal potential output in the presence of pests times damage, or

$$\left(1-g\left(b^r,z,k,t,s\right)\right)\pi_1\left(pg\left(b^r,z,k,t,s\right),w,k,t,s\right).$$

Subtracting this latter pest-loss measure from $\frac{R}{p}$ gives the following measure of the difference between the two loss measures

$$D^{Rg}\left(pg\left(b^r,z,k,t,s\right),w,k,t,s\right):=\pi_1(p,w,k,t,s)-\pi_1\left(pg\left(b^r,z,k,t,s\right),w,k,t,s\right)\geq 0.$$

The inequality follows because restricted profit is convex in output price and $p \geq pg$. Hence, we conclude that $\left(1-g\left(b^r,z,k,t,s\right)\right)\pi_1\left(pg\left(b^r,z,k,t,s\right),w,k,t,s\right)$ *understates the output loss associated with the presence of pests.*The amount that the traditional measure of output loss understates the true economic output loss equals the difference between maximal potential output in the absence of pests and maximal potential output in the presence of pests.

Expressing loss in percentage terms, notice that

$$(4)\qquad \frac{y(p,w,k,b^r,z,t,s)}{y(p,w,k,0,0,t,s)}=\frac{\pi_1\left(pg\left(b^r,z,k,t,s\right),w,k,t,s\right)}{\pi_1(p,w,k,t,s)}g\left(b^r,z,k,t,s\right)\leq g\left(b^r,z,k,t,s\right),$$

where the inequality follows because $\pi_1(p,w,k,t,s)\geq\pi_1\left(pg\left(b^r,z,k,t,s\right),w,k,t,s\right)$. Accordingly, $1-g\left(b^r,z,k,t,s\right)\leq 1-\frac{y(p,w,k,b^r,z,t,s)}{y(p,w,k,0,0,t,s)}$. Thus, *we conclude that the traditional damage measure understates both the percentage of output and the percentage of revenue loss caused by pests.*

The economic explanation is as follows. A nonzero pest infestation, $b^r>0$, ensures that there will be some pest damage. Damage-control activities can mitigate this output loss, but the loss is only entirely averted when z is applied at levels that ensure $g(b^r, z, k, t, s) = 1$. A rational farmer, realizing that variable-input use in the presence of the pest infestation is less profitable than its absence, responds by lowering his or her *maximal potential output* from $\pi_1(p, w, k, t, s)$ to $\pi_1(pg(b^r, z, k, t, s), w, k, t, s)$ because $pg(b^r, z, k, t, s) \leq p$. *In the asymmetric specification, a farmer's rational response to the presence of pests is isomorphic to his or her rational response to a decrease in the price of output.* Maximal potential supply adjusts downward. This curtailment of maximal potential supply, which represents a true economic loss, is not captured by $g(b^r, z, k, t, s)$. Because the downward supply adjustment induced by the presence of the pest is ignored, the revenue and output loss is understated.

In examining $D^{Rg}(pg(b^r, z, k, t, s), w, k, t, s)$, one sees that the difference approaches zero as g approaches one, that is, as the traditional damage measure becomes relatively small. But as the traditional damage measure grows (g declines), the divergence between the two measures grows at a rate governed by the elasticity of supply for maximal potential supply. The greater that elasticity, the greater is $D^{Rg}(pg(b^r, z, k, t, s), w, k, t, s)$, and thus the greater the bias that will be realized as a consequence of using $1 - g$ to measure damage.

We now compare $1-g(b^r, z, k, t, s)$ and the quasi-rent loss measure in percentage terms, $q(p, w, k, b^r, z, t, s)$. Subtracting $1-g(b^r, z, k, t, s)$ from $q(p, w, k, b^r, z, t, s)$ gives (after dropping function arguments on $g(b^r, z, k, t, s)$ for notational compactness)

$$\begin{aligned}
q - (1-g) &= 1 - \frac{\pi(pg, w, k, t, s)}{\pi(p, w, k, t, s)} - 1 + g \\
&= g - \frac{\pi(pg, w, k, t, s)}{\pi(p, w, k, t, s)} \\
&= \frac{g\pi(p, w, k, t, s) - \pi(pg, w, k, t, s)}{\pi(p, w, k, t, s)} \\
&= \frac{\pi(pg, wg, k, t, s) - \pi(pg, w, k, t, s)}{\pi(p, w, k, t, s)} \\
&\geq 0.
\end{aligned}$$

The fourth equality, which is crucial in this derivation, follows from the positive linear homogeneity of restricted-profit functions in input and output prices. The final inequality then follows because the restricted-profit function is nonincreasing in input price and $g(b^r, z, k, t, s) \leq 1$.

Thus, $(1-g)$ underestimates, in percentage terms, the quasi-rent loss due to the presence of pests, q. What about actual losses in dollar terms? The traditional damage measure in dollar terms is output price times the quantity loss

$$p(1 - g(b^r, z, k, t, s))\,\pi_1(pg(b^r, z, k, t, s), w, k, t, s).$$

Subtracting this measure from $Q(p, w, k, b^r, z, t, s)$ gives the following measure of the bias expressed as a function of g

$$B(g) = \pi(p, w, k, t, s) - \pi(pg, w, k, t, s) - p(1-g)\,\pi_1(pg, w, k, t, s).$$

Using Hotelling's lemma and our definitions allows us to rewrite this expression to

$$\begin{aligned}
(5) \qquad B(g) \quad &: = p[\pi_1(p, w, k, t, s) - \pi_1(pg, w, k, t, s)] + w'[\pi_w(p, w, k, t, s) - \pi_w(pg, w, k, t, s)] \\
&= p[\pi_1(p, w, k, t, s) - \pi_1(pg, w, k, t, s)] - C(p, w, k, b^r, z, t, s)
\end{aligned}$$

as the difference between quasi-rent loss due to pests and the traditional dollar measure of pest damage. The first term in this expression, $p[\pi_1(p, w, k, t, s) - \pi_1(pg, w, k, t, s)]$, which is the dollar amount that the traditional damage measure underestimates actual revenue loss, is necessarily positive as already shown.

The second term in (5), $C(p, w, k, b^r, z, t, s)$, is also positive. For smooth technologies, this is established as follows. Differentiating $w'\pi_w(p, w, k, t, s)$ with respect to p gives $w'\pi_{w1}(p, w, k, t, s)$, which by Young's theorem on symmetry of partial derivatives equals $w'\pi_{1w}(p, w, k, t, s)$. The positive linear homogeneity of $\pi(p, w, k, t, s)$ implies, however, that $w'\pi_{1w}(p, w, k, t, s)$ equals $-p\pi_{11}(p, w, k, t, s)$, which in turn, is negative by convexity of the restricted-profit function. Hence, $w'\pi_w(p, w, k, t, s)$ is decreasing in p, and, thus, $C(p, w, k, b^r, z, t, s)$ must be nonnegative.

In more economic terms, the presence of pests ensures the presence of some damage. As already shown, rational producers respond by lowering their maximal planned output. This supply reduction evokes a cost saving, which is captured by $C(p, w, k, b^r, z, t, s)$, as rational producers reduce their use of some inputs and rearrange the utilization of other inputs.

Thus, whether the traditional measure of damage value understates or overstates the true economic value of pest damage depends upon the relative magnitudes of the two positive terms in (5). Notice, however, that for smooth technologies $\lim_{g\to 1} B(g) = 0$, while differentiation establishes

$$B'(g) = -p^2(1-g)\pi_{11}(pg, w, k, t, s) \leq 0,$$

by the convexity of restricted profit in variable input and output prices. Therefore, for smooth technologies the damage measures are approximately the same as long as damage is relatively small (g is close to 1), but $B(g)$ becomes increasingly positive as damage increases (g decreases) at a rate that is governed by the elasticity of supply. The more elastic is supply, the quicker the divergence grows. Moreover, under the presumption that $\lim_{p\to 0}\pi_1(p, w, k, t, s) = 0$, that is profit maximizing supply for a zero output price is zero, then $\lim_{g\to 0} B(g) = \pi(p, w, k, t, s)$.

We have shown that the traditional damage measure, $1-g$, always understates both revenue loss and quasi-rent loss in both absolute and percentage terms. The only comparison that remains is between $Q(p, w, k, b^r, z, t, s)$ and $R(p, w, k, b^r, z, t, s)$. It was established above that $C(p, w, k, b^r, z, t, s) > 0$, from which it follows that $R(p, w, k, b^r, z, t, s) \geq Q(p, w, k, b^r, z, t, s)$. The economic reason, of course, is that revenue loss ignores the cost saving that is associated with rational profit maximizing producers conserving on variable cost as a consequence of their rational supply reduction.

In percentage terms, the comparison seems less clear cut. We wish to compare (again suppressing g subscripts)

$$1 - \frac{\pi(pg, w, k, t, s)}{\pi(p, w, k, t, s)}$$

and

$$1 - \frac{pg\pi_1(pg, w, k, t, s)}{p\pi_1(p, w, k, t, s)}.$$

Provided $\dot{g} > 0$, the percentage profit loss is greater than the percentage revenue loss if and only if

$$\begin{aligned}\frac{p\pi_1(pg, w, k, t, s)}{\pi(pg, w, k, t, s)} &\geq \frac{p\pi_1(p, w, k, t, s)}{g\pi(p, w, k, t, s)} \\ &= \frac{p\pi_1(p, w, k, t, s)}{\pi(pg, wg, k, t, s)} \\ &= \frac{p\pi_1(pg, wg, k, t, s)}{\pi(pg, wg, k, t, s)}.\end{aligned}$$

The first equality follows from the positive linear homogeneity of restricted-profit functions, as does the second. Alternatively, the second can be recognized, via Hotelling's lemma, as a consequence of the fact that optimal supply is homogeneous of degree zero in (p, w) and thus $\pi_1(pg, wg, k, t, s) = \pi_1(p, w, k, t, s)$

for $g > 0$. Economically, for this condition to be satisfied, revenue share's in quasi-rent must decrease as a resulting of radially reducing all variable input prices by the traditional damage measure. Put another way, revenue must increase less in percentage terms than quasi-rent as a result of such a rescaling of variable input prices.

3 Marginal Returns and Biases

A primary thrust of the empirical debate on pesticide productivity concerns the appropriate measurement of the shadow prices (marginal returns, marginal productivity) of damage-control agents. For a smooth technology with a quasi-fixed input endowment of k, the shadow prices of the damage-control agents, z, are their marginal contributions to quasi-rent (variable profit):

$$\Pi_z\left(p, w, k, b^r, z, t, s\right) = \pi_1\left(pg\left(b^r, z, k, t, s\right), w, k, t, s\right) pg_z\left(b^r, z, k, t, s\right), \tag{6}$$

where Π_z denotes the gradient of Π with respect to z and g_z denotes the gradient of g with respect to z. Because $\pi_1\left(pg\left(b^r, z, k, t, s\right), w, k, t, s\right) g\left(b^r, z, k, t, s\right)$ is realized optimal supply in the presence of pests, each component of $\Pi_z\left(p, w, k, b^r, z, t, s\right)$, thus, equals the marginal revenue associated with a small change in the use of the associated damage-control agent.

To determine how the shadow prices of damage-control agents adjust to changes in their usage, we examine

$$\Pi_{zz}\left(p, w, k, b^r, z, t, s\right) = \pi_{11} p^2 g_z g_z' + \pi_1 p g_{zz}, \tag{7}$$

where Π_{zz} and g_{zz} are the Hessian matrices of Π and g, respectively, in z. In the asymmetric specification, changes in z, thus, have two distinct effects on its shadow price.

These different effects are most easily illustrated in the case of a single damage-control input. In that case, an increase in z changes damage control (damage) at the margin by g_z $(-g_z)$. If the damage-control agent's marginal product is positive, damage control increases marginally by g_z. In the asymmetric specification, this is equivalent to increasing the "effective price" of the commodity, pg, by pg_z. This increase in the effective price of the output, which is the result of a greater percentage of maximal output being realized *while holding variable inputs constant,* elicits a positive supply response. That supply response yields more revenue at prevailing prices. This effect is measured by the term, $\pi_{11} p^2 g_z g_z'$, in expression (7).

Increasing z at the margin, however, also changes its marginal effectiveness in controlling pests, and this change is captured by g_{zz}. If there are increasing returns (marginal productivity) to pesticide use, as usually interpreted in the pesticide-productivity literature, then $g_{zz} > 0$. If there are diminishing returns (marginal productivity) then $g_{zz} < 0$. Virtually all of the debate in the literature on pesticide productivity on marginal returns has centered on whether this component of the overall effect is positive or negative. Our empirical specification, following Fox and Weersink (1995), allows for either $g_{zz} < 0$ or $g_{zz} > 0$.[4]

Because of the supply-response effect, diminishing marginal returns in the usual sense, that is, $g_{zz} < 0$, is not sufficient to ensure that $\Pi_{zz} \leq 0$. For that to be true in the single damage-control input case, it must be true that

$$\frac{\pi_{11} p}{\pi_1} \leq -\frac{g_{zz}}{g_z^2}. \tag{8}$$

[4] Hennessy (1997) presents a detailed analysis of the conditions required for g to exhibit increasing or decreasing marginal returns in z in the Fox and Weersink (1995) specification.

The left-hand side, by Hotelling's Lemma, is the elasticity of supply while the right-hand side measures the flexibility of g_z to changes in the use of the damage-control agent. Our empirical specification that follows does not predetermine either the elasticity of supply or the flexibility of g_z.[5]

Expression (6) is, perhaps, the most obvious way to think about shadow prices of damage-control agents. But another interpretation is available. From (1),

$$\begin{aligned}\Pi(p, w, k, b^r, z, t, s) &= \pi(pg(b^r, z, k, t, s), w, k, t, s) \\ &= \pi_k(pg(b^r, z, k, t, s), w, k, t, s)' k.\end{aligned}$$

Hence, for damage-control agent z

$$\Pi_z(p, w, k, b^r, z, t, s) = p\frac{\partial g(b^r, z, k, t, s)}{\partial z}\pi_{k1}(pg(b^r, z, k, t, s), w, k, t, s)' k,$$

where $\pi_{k1}(pg(b^r, z, k, t, s), w, k, t, s)$ denotes the vector composed of the partial derivatives of each shadow price for the elements of k with respect to pg. Hence, the shadow price of damage-control agent can be decomposed into that damage-control agent's marginal contributions to the quasi rents attributable to k.

Another perspective on this decomposition follows by noting that the Clark-Wicksteed product exhaustion theorem implies:

$$\begin{aligned}\frac{\pi_k(pg(b^r, z, k, t, s), w, k, t, s)' k}{\Pi(p, w, k, b^r, z, t, s)} &= \frac{\pi_k(pg(b^r, z, k, t, s), w, k, t, s)' k}{\pi(pg(b^r, z, k, t, s), w, k, t, s)} \\ &= \sum_{v=1}\frac{\partial \ln \pi(pg, w, k, t, s)}{\partial \ln k_v} \\ &= 1.\end{aligned}$$

Shares of the fixed factors in total quasi rent must sum to one. Differentiating this distribution rule with respect to, say, z_u gives

$$\begin{aligned}\frac{\partial}{\partial z_u}\left(\sum_{v=1}\frac{\partial \ln \pi(pg, w, k, t, s)}{\partial \ln k_v}\right) &= \sum_{v=1}\frac{\partial^2 \ln \pi(pg, w, k, t, s)}{\partial \ln k_v \partial(pg)} p\frac{\partial g(b^r, z, k, t, s)}{\partial z_u} \\ &= 0,\end{aligned}$$

which establishes how changing z_u affects the *distribution* of quasi rent across the quasi-fixed factors of production. Thus, if $\frac{\partial^2 \ln \pi(pg,w,k,t,s)}{\partial \ln k_v \partial(pg)} p\frac{\partial g(b^r,z,k,t,s)}{\partial z_u} > 0$, marginal applications of z_u increase k_v's share of quasi rent and decrease it otherwise. Therefore, we shall say in the following that damage control agent z_u *enhances* the quasi rents to quasi-fixed factor, k_v, if $\frac{\partial^2 \ln \pi(pg,w,k,t,s)}{\partial \ln k_v \partial(pg)} p\frac{\partial g(b^r,z,k,t,s)}{\partial z_u} > 0$ and *diminishes* the quasi rent otherwise. A damage-control agent enhances the quasi-rent to k_v only if marginal applications of the damage-control agent increase k_v's quasi rent more in percentage terms than they increase total quasi rent, $\Pi(p, w, k, b^r, z, t, s)$ in percentage terms.

Whether damage-control agents enhance or diminish the returns to the various quasi-fixed factor yields potentially important information on how damage-control agents interact with quasi-fixed factors in the production process. One can, of course, define a similar decomposition for how output and variable input shares in total quasi-rent are affected by changes in application rates of damage-control inputs. Such a decomposition, by convoluting supply adjustment and input adjustments, partially disguise the manner in

[5] Notice, however, that in the presence of linear pricing of the damage-control agents, $\Pi_{zz} \leq 0$ is required in the neighborhood of any well-defined profit maximizing equilibrium.

which variable inputs interact with one another, and how that interaction is affected by the application of pesticides.

To examine the interaction between variable inputs in a fashion that is directly comparable to the standard notion of substitution and complementary behavior among inputs, we examine how z affects the optimal allocations of cost shares across variable inputs *for a given level of realized output.* By Shephard's Lemma, the cost-minimizing demand for the jth variable input, when realized output is $\bar{y}$, pest infestation is b^r, and damage-control agents are applied at z, is

$$\frac{\partial}{\partial w_n} c\left(w, \frac{\bar{y}}{g\left(b^r, z, k, t, s\right)}, k, t, s\right),$$

and the positive linear homogeneity of variable costs in variable input prices ensures that the sum of individual variable-factor cost sum to variable cost:

$$\sum_n w_n \frac{\partial}{\partial w_n} c\left(w, \frac{\bar{y}}{g\left(b^r, z, k, t, s\right)}, k, t, s\right) = c\left(w, \frac{\bar{y}}{g\left(b^r, z, k, t, s\right)}, k, t, s\right).$$

Dividing both sides by variable cost and rewriting the result in terms of logarithms gives:

$$\sum_n \frac{\partial}{\partial \ln w_n} \ln c\left(w, \frac{\bar{y}}{g\left(b^r, z, k, t, s\right)}, k, t, s\right) = 1,$$

with each

$$\frac{\partial}{\partial \ln w_n} \ln c\left(w, \frac{\bar{y}}{g\left(b^r, z, k, t, s\right)}, k, t, s\right)$$

interpretable as the nth variable-input's share in variable cost.

Thus, at the margin for each damage-control agent, z_u

$$\sum_n \frac{\partial^2}{\partial \ln w_n \partial z_u} \ln c\left(w, \frac{\bar{y}}{g}, k, t, s\right) = 0,$$

with

$$\frac{\partial^2}{\partial \ln w_n \partial z_u} \ln c\left(w, \frac{\bar{y}}{g}, k, t, s\right),$$

interpretable as the marginal effect of the damage-control agent on the nth variable input's cost share. If marginal changes in z_u increase the nth variable-input's cost share, we will say that application of the damage-control agent is input n using because it promotes a greater relative utilization of input n than prior to application. Conversely, if

$$\frac{\partial^2}{\partial \ln w_n \partial z_u} \ln c\left(w, \frac{\bar{y}}{g}, k, t, s\right)$$

is negative, we will say that the damage-control agent is input n saving because its application promotes a smaller relative utilization of input n. Applications of a damage-control input are input n saving only if marginal applications of the damage-control input cause input n's wage bill to fall more in percentage terms than it reduces (in percentage terms) variable-cost of all the non-damage-control, variable inputs. As an intuitive example of input n saving damage-control agents, one might think in terms of herbicides applied to control weed growth. If weed clearing in the absence of the herbicide required hand pulling, one would expect the herbicide to be labor saving.

4 Data

The data used in our empirical analysis are for olive production and were obtained from the Greek National Agricultural Research Foundation (NAgReF). The data consist of a panel of observations drawn from forty-five (45) olive-growing farms located in the western part of the Greek island of Crete. Between 1999 and 2004, extension agents from the NAgReF undertook a small-scale survey designed to investigate the effectiveness of six different pesticide ingredients against the olive-fruit fly *Bactrocera oleae* (Gmellin). *Bactrocera oleae* is the only significant pest that attacks olive trees. It burrows into the fruit, where it then reproduces (May, beginning of June). Infected fruit fall to the ground well before they mature. During the May-October cropping season, the fly has three or four different biological cycles depending on the prevailing environmental and climatic conditions. High humidity and air temperature levels encourage larger pest populations.

The surveyed farms were all located in the same geographical area in the western part of Crete. That portion of Crete is quite specialized in olive-tree cultivation. The different pesticide materials were applied approximately every two weeks in response to observations on the existing pest populations. Pest population was measured using chemical traps installed on every 500 m^2 of the farm's plot. The number of flies captured was then extrapolated to obtain a measure of the whole pest population for each farm. The data set also contains information on production volumes, input expenses, as well as a number of farm-specific variables including demographic characteristics, environmental conditions and extension services provision. Summary statistics of the variables are presented in Table 1.

One output and three variable inputs were distinguished. Output includes olive-oil quantities sold off the farm plus quantities consumed in farm households during the cropping year. The price of olive-oil is that obtained by farmer at the date that farm production is sold to the market, adding subsidies and subtracting indirect taxes. Because Greece is the third largest olive-oil producing country after Spain and Italy, the prices exhibit considerable variation during the same cropping year. The perennial feature of olive-tree (good cropping years are followed by less productive ones) and differences in cropping seasons across the three major producing countries results in very variable prices for olive oil at the farmgate.

The variable inputs are labour, chemical fertilizers, and intermediate inputs. Data on the labor input consist of hours worked disaggregated by hired, self-employed, and unpaid family workers. Compensation of hired farm workers is defined as the average hourly wage plus social security taxes paid by farmers. Labor compensation data are not directly available for self-employed and unpaid family workers. Therefore, self-employed and unpaid family workers are imputed the mean wage earned by hired farm workers. Olive farmers utilize a mixture of chemical fertilizers depending on the soil quality and specific needs of their trees. These include nitrate, phosphorous and potassium fertilizers that are applied after the harvesting season (January-March). The aggregate price of fertilizers was computed using a Divisia index with the cost-shares of each one of the different fertilizers used as weights. Finally, the intermediate input consists of goods used in olive-oil production during the cropping year, whether purchased from outside the farm or withdrawn from beginning inventories. These include fuel and electric power, storage expenses, irrigation water, measured in euros. Again the aggregate price of intermediate inputs was computed using Divisia methods, and the aggregate quantity was then obtained.

The quasi-fixed inputs used in the analysis are land devoted to olive-tree cultivation, measured in stremmas (1 stremma equals 0.1 hectare), and capital stock. Capital stock observations were computed using the perpetual-inventory method as described by Ball et al. (1993). The damage-control agent includes the different pesticide materials measured in litres converted into a single index. There are also data on farm-specific characteristics. These include data on the farmer'e education level, measured in years of formal schooling, the number of extension visits per farm, an aridity index defined as the ratio of the average temperature in the area where the farm is located over the total precipitation in the same area (Stallings, 1960).

To avoid problems associated with units of measurement, all variables were converted into indices, with the basis for normalization being the representative olive-growing farm. The choice of the representative farm was based on the smallest deviation of the variables (i.e. output and input levels) from the sample means.

5 The Econometric Specification

We chose the following transcendental logarithmic (translog) specification for $\pi(p, w, k, t, s)$:

$$
\begin{aligned}
(9)\ \ln \pi_{it}(p_{it}, w_{it}, k_{it}, t, s_{it}) &= \alpha_0 + \alpha^p \ln p_{it} + \sum_j \alpha_j^w \ln w_{jit} + \sum_v \alpha_v^k \ln k_{vit} + \sum_h \alpha_h^s \ln s_{hit} + \alpha^t t \\
&+ \frac{1}{2}\left[\alpha^{pp}(\ln p_{it})^2 + \sum_j \sum_n \alpha_{jn}^{ww} \ln w_{jit} \ln w_{nit} + \alpha^{tt} t^2\right] \\
&+ \frac{1}{2}\left[\sum_v \sum_q \alpha_v^{kk} \ln k_{vit} \ln k_{qit} + \sum_h \sum_c \alpha_{hc}^{ss} \ln s_{hit} \ln s_{cit}\right] \\
&+ \ln p_{it}\left[\sum_j \alpha_j^{wp} \ln w_{jit} + \sum_v \alpha_v^{kp} \ln k_{vit} + \sum_h \alpha_h^{sp} \ln s_{hit} + \alpha^{tp} t\right] \\
&+ \sum_j \sum_v \alpha_{jv}^{wk} \ln w_{jit} \ln k_{vit} + \sum_j \sum_h \alpha_{jh}^{ws} \ln w_{jit} \ln s_{hit} + t \sum_j \alpha_j^{wt} \ln w_{jit} \\
&+ \sum_v \sum_h \alpha_{vh}^{ks} \ln k_{vit} \ln s_{hit} + t \sum_v \alpha_v^{kt} \ln k_{vit} + t \sum_h \alpha_h^{st} \ln s_{hit}
\end{aligned}
$$

with $\alpha_{jn}^{ww} = \alpha_{nj}^{ww}, \alpha_{hc}^{ss} = \alpha_{ch}^{ss}, \alpha_{vq}^{kk} = \alpha_{qv}^{kk},\ \alpha^p + \sum_j \alpha_j^w = 1,\ \alpha^{pp} + \sum_j \alpha_j^{wp} = 0,\ \alpha_v^{kp} + \sum_j \alpha_{jv}^{wk} = 0$ for all v, $\alpha_h^{sp} + \sum_j \alpha_{jh}^{ws} = 0$ for all h, and $\alpha^{tp} + \sum_j \alpha_j^{wt} = 0$. Here subscript i indexes the farm, subscript t indexes the time period, and t is a simple time trend variable. To ensure that (1) is satisfied, we also impose $\sum_v \alpha_v^k = 1, \sum_v \alpha_{vq}^{kk} = 0$ for all $q, \sum_v \alpha_{jv}^{wk} = 0$ for all j, $\sum_v \alpha_v^{kp} = 0$, and $\sum_v \alpha_{vh}^{ks} = 0$ for all h.

Our econometric specification of g follows the contribution of Fox and Weersink (1995), which decomposes g into two components and thus allows for the possibility of increasing returns to the damage-control agent:

$$
(10) \qquad g_{it} = 1 - \exp\left(\lambda b_{it}^r (1 - \phi_{it})\right),
$$

where[6]

$$
\phi_{it} = 1 - \exp\left(-\beta^z z_{it} - \beta^{tz} z_{it} t - \sum_h \beta^{zs} z_{it} s_{hit}\right).
$$

Upon subsituting (10) into (9) to obtain $\ln \pi_{it}(p_{it} g_{it}, w_{it}, k_{it}, t, s_{it})$, Hotelling's Lemma implies that the associated supply and variable-input demands in quasi-rent share form are given by

$$
\begin{aligned}
S_{it}^p &= \alpha^p + \alpha^{pp}(\ln p_{it} + \ln g_{it}) + \sum_j \alpha_j^{wp} \ln w_{jit} + \sum_v \alpha_v^{kp} \ln k_{vit} + \sum_h \alpha_h^{sp} \ln s_{hit} + \alpha^{tp} t \\
-S_{it}^j &= \alpha_j^w + \sum_n \alpha_{jn}^{ww} \ln w_{nit} + \alpha_j^{wp}(\ln p_{it} + \ln g_{it}) + \sum_v \alpha_{jv}^{wk} \ln k_{vit} + \sum_h \alpha_{jh}^{ws} \ln s_{hit} + \alpha_j^{wt} t,
\end{aligned}
$$

[6] After some experimentation k was not included in the econometric specification of ϕ.

where S_{it}^{p} denotes the revenue share in quasi rent and S_{it}^{j} denotes the share of the jth variable factor in quasi rent.

6 Estimation

Because of the nonlinearity imposed by our damage-control specification (10), the system of supply and variable-input demand profit shares has been estimated together with the profit function using the full-information-maximum-likelihood (FIML) method after appending a suitable econometric error structure to our specification. The associated likelihood function was maximized using the Berndt, Hall, Hall, and Hausman (BHHH) algorithm. The FIML estimator has the same asymptotic properties as the three-stage least squares estimator, and with normally distributed disturbances it is asymptotically efficient (Hausman, 1975). The price of intermediate inputs and the level of cultivated land were used as numeraires in imposing linear homogeneity in crop and input prices and in quasi-fixed inputs, respectively.

Although our theoretical specification treats application of the damage-control agent (pesticides) as a quasi-fixed input, its observed values are subject to producer choice and, thus, endogenous econometrically. To correct for the potential biases, we ran a first-stage regression of pesticide use against a set of environmental and farmer-specific variables together with the level of pest infestation (summary statistics of the variables are provided in Table 1). Specifically, as environmental variables we used the average temperature and humidity levels in the field as well as the altitude of farm location. High temperature and humidity levels affect pest population by creating more favorable environmental conditions for their occurence. On the other hand, the higher the altitude the lower will be the pest population. Farmer-specific characteristics, such as the level of education and the provision of extension activities affect the farmer's understanding of proper pesticide application. Educated farmers can more easily digest technical information associated with appropriate pesticide application. At the same time extension visits on farm by extension agents may provide useful information to farmers on the pest infestation, the maturity stage of pests that also affect pesticide application. The predicted value of pesticide application obtained from the first-stage regresssions was used in the econometric estimation of the system of supply and variable-input demands (the parameter estimates of the first-stage regression are available from the authors upon request).

7 Empirical Results

Estimated values for the parameters of our econometric model are reported in Table 2. These results indicate that the model fits these data quite well and most parameters are quite precisely estimated.

The estimated supply and input-demand functions are consistent with theory as evidenced by their implied elasticities reported (at sample means) in the upper panel of Table 3. Specifically, each variable input demand equation is downward sloping in its own price, and the supply elasticity for olives is positive and of reasonable magnitude (.894). The input demand elasticities all appear to be of plausible magnitudes, but we do note that the own-price demand elasticity for intermediate inputs is somewhat higher than that for either fertilizer or labor. Notice, however, that the estimated elasticity of supply with respect to the price of intermediate inputs is also quite large and negative suggesting that much of the responsiveness of intermediate inputs to changes in variable input prices is actually due to a large output effect (more on this below). All inputs are nonregressive (normal) in the sense that profit-maximizing input demand elasticities with respect to the output price are positive and, thus, all supply elasticities with respect to variable input prices are negative. All variable inputs are found to be gross complements.

To investigate the pattern of substitution and complementarity more closely, we remove, following Sakai (1974), Lopez (1984) and Chambers (1988, p. 134), the output effect from the profit maximizing input demands and compute the compensated (constant output, cost minimizing) input demand elasticities for the variable inputs that are implied by our estimated profit function. These elasticities, which provide qualitatively the same information as the Allen (one-price, one-factor) elasticities of substitution, are reported in the middle panel of Table 3 while the associated Morishima (two-price, one-factor) elasticities of substitution for the estimated system (Mundlak, 1968; Ball and Chambers, 1981; Chambers, 1988; and Blackorby and Russell, 1989) are presented in the lower panel of Table 3. The reported elasticities are consistent with theory. All compensated input demands are downward sloping in their own price. Moreover, removal of the supply-expansion effect reveals that all variable inputs are net substitutes for one another using either the one-price, one factor or the Morishima elasticity. Notice, in particular, that the compensated demand elasticity of intermediate inputs is much smaller than the associated uncompensated demand elasticity confirming our earlier statement that much of the associated uncompensated input-demand responsiveness is due to an important and large output effect suggesting that, for our sample, intermediate input usage is largely driven by the level of the olive crop planned by the farmer.

The upper panels of Table 4 summarizes our empirical results on the alternative measures of pest damage: quasi-rent loss, $Q(p, w, k, b^r, z, t, s)$, the revenue-cost decomposition of quasi-rent loss, $R(p, w, k, b^r, z, t, s)$ and $C(p, w, k, b^r, z, t, s)$, the physical damage to the crop that would have occured in the absence of pesticide application, $1 - g(b^r, 0, k, t, s)$, the crop loss due to the presence of pests, $1 - \frac{y(p,w,k,b^r,z,t,s)}{y(p,w,k,0,0,t,s)}$, the conventional output damage measure $(1 - g(b^r, z, k, t, s))$, and economic damage measure (quasi-rent loss) in percentage terms. These results are reported at sample means and by profit-quartile averages.

As Table 4 illustrates, the quasi-rent loss, $Q(p, w, k, b^r, z, t, s)$, for all profit quartiles and the average farm is smaller than the revenue effect, $R(p, w, k, b^r, z, t, s)$. As our theoretical results demonstrate, the difference emerges from the cost adjustment, $C(p, w, k, b^r, z, t, s)$, in terms of planned supply and variable inputs that farmers make as a result of the lower "effective" output price caused by the presence of pests. The empirical results also confirm that profit maximizing crop loss due to the presence of pests, $1 - \frac{y(p,w,k,b^r,z,t,s)}{y(p,w,k,0,0,t,s)}$), exceeds $1 - g(b^r, z, k, t, s)$ (as our theory indicates) and the economic damage from pests for all profit quartiles and the average farm. It is less, however, than the damage that would occur to planned output in the absence of pesticide applications. At sample means, physical crop damage (without pesticide application), the profit maximizing crop loss due to pests, physical crop damage (with pesticides), and economic damage are, respectively, 19.63%, 18.52%, 17.38%, and 11.55%. Thus, on average, the application of pesticides reduces physical crop damage by a little over two percentage points from 19.63% to 17.38%. Economic damage is roughly 2/3 of both $1 - \frac{y(p,w,k,b^r,z,t,s)}{y(p,w,k,0,0,t,s)}$ (crop loss due to pests) and physical crop damage (with pesticides). And crop lost as a result of the presence of pests, $1 - \frac{y(p,w,k,b^r,z,t,s)}{y(p,w,k,0,0,t,s)}$, in percentage terms is about 1.1 points greater than physical crop damage for the sample average (18.52% compared to 17.38%).

In economic terms, the finding for our data set that economic damage is only about 2/3 as large as physical crop damage, $1 - g(b^r, z, k, t, s)$, is particularly interesting. It suggests that the latter dramatically overstates the actual economic damage that the presence of pests incurs for our sample of farms. Our empirical results suggest that the olive farmers in our sample are much more effective at coping with pests than conventional measures applied to the same data set might suggest. The conventional damage measure only captures how much damage pests do to physical supply of the commodity produced, while it ignores the farmer's rational response to profit incentives in other dimensions of his or her farming activities. The result, for our data set, is a serious overstatement of pest damage and an understatement of the effectiveness of current pesticide practices.

Neither our theory or our empirical results allow us to extrapolate these results beyond our case study. However, these empirical findings and our theory do suggest that other studies of pest damage and pesticides may suffer from similar dramatic biases in their results and that the potential for such biases should be taken seriously in theoretical, empirical, and practical policy analyses of this issue.

All crop-loss measures increase over profit quartiles while economic damage increases over the first three quartiles and then declines (slightly) from the third to the fourth. This suggests for our data set that the difficulty of controlling for pests may increase with farm size. This may also partially explain why larger farms in our sample often use pesticides more intensively than less profitable operations.

Having said this, it is interesting to note, however, that the largest farmers are also the most productive users of pesticides which in turn implies that they use the cooperating inputs more effectively in combination with pesticides than the smaller farmers. The bottom panel of Table 4 shows that both proposed measures of pesticide productivity are increasing across profit quartiles. In particular, the physical pesticide productivity measure for the largest profit quartile is 28 times larger than that for the smallest quartile, 8 times larger than the second, and almost 4 times larger than the third quartile. Notice also that, as was expected, the average product overstates the contribution of pesticides to actual output because some production will survive even without pesticide application.

Table 5 reports estimates of the shadow price of pesticides. Table 6 reports estimates of the flexibilities of the shadow prices of pesticides, land, and capital with respect to fixed inputs and to variable input prices. The estimated own flexibilities for pesticides, land, and capital exhibit are all negative. Thus, although our empirical specification was specifically chosen, following Fox and Weersink (1995), to permit the presence of increasing marginal pesticide productivity, we find that marginal returns (marginal quasi rents) for pesticides are decreasing for our data set. It, therefore, follows immediately from (8) that marginal pesticide productivity is also decreasing for our data set. Table 6 also reveals that pesticides, land, and capital all have shadow prices that are decreasing in all the variable input prices. An application of Hotelling's lemma thus reveals that increased use of pesticides, land, and capital all tend to increase the utilization of each of the variable factors of production.

In considering the shadow price of pesticides more closely, one sees several patterns to emerge. First, there is considerable variability in the shadow price of pesticides across farms. Second, marginal returns to pesticides grow steadily over profit quartiles and become very large for the highest profit quartile (see Table 5). This is closely related to our previous findings that the largest farmers are the most productive users of pesticides and that the need for pesticides increases with output, which result in larger returns at higher profit quartiles. Third, for all farms and thus all quartiles, the largest component of marginal returns to pesticides are marginal enhancements to the quasi-rents of capital with a much smaller component coming from marginal enhancements to quasi-rents of land. But even though the largest component of marginal returns to pesticides comes from enhancements to capital quasi-rents, pesticides for all farms and all profit quartiles are land-enhancing and capital-diminishing. Thus, marginal applications of pesticides tend to increase land's share of quasi rent and decrease capitals. Table 5 also reports the pesticide biases for each of the variable inputs. Over all quartiles, pesticides are labor and fertilizer using and intermediate materials saving. Thus, even though increased pesticides usage is associated with increased usage of labor, fertilizer, and intermediate inputs (as Table 6 indicates), the relatively greater percentage increase (in cost share terms) is for labor and fertilizer than for intermediate inputs.

8 Concluding Remarks

Using the Lichtenberg-Zilberman-Fox-Weersink damage specification, we have developed a short-run, supply-response framework based on profit maximizing producer behavior in the presence of damage agents. We have shown how that representation can be used to measure and decompose the economic damage associated with the presence of pests, how to measure the shadow prices of damage-control agents, how to measure the manner in which pesticide application biases variable input use, and how pesticide application affects the relative returns to quasi-fixed factors of production.

Using a panel data set on Greek olive producers, we have estimated an econometric version of our model, and obtained empirical estimates of the various effects for our model. Our empirical results ??????????????????????????????????

The empirical methodology that we employ represents an extension of the dual approach used by Chambers and Lichtenberg (1994) that accommodates the Fox and Weersink (1995) extension of the Lichtenberg and Zilberman (1986) asymmetric damage specification. Our data set, which contains observations on pest infestations, allows us to incorporate such measures directly into the empirical representation of pest damage. Frequently, such data will not be available in conjunction with data on inputs and outputs produced under actual field conditions. For example, the Chambers and Lichtenberg (1994) empirical analysis is based upon a data set that does not contain such information. In such cases, naturally, one cannot implement exactly the same empirical specification and procedure as used here. However, one can suitably adjust our methods, while still accommodating the Fox and Weersink (1995) specification, to such data and still obtain empirical estimates of optimal maximal physical output in the absence and presence of pests, quasi rents in the presence and absence of pests, and marginal productivity of pesticides. Of course, one expects such estimates to be less precise in the absence of a richer data set, but they are still available empirically.

Both our theoretical and empirical results have potential implications for pesticide policy and pesticide practice. There are also obvious caveats. For example, as a reviewer points out, our empirical results apply to the technical practices actually employed by farmers under the assumption that farmers are rational profit maximizers. As a result, they are not directly comparable to results that are based on the analysis of damage data drawn from experimental trials in controlled situations for at least two reasons. One, the specific technology applied under controlled experimental situations may not correspond to the technical practices that are actually used by farmers in actual operating conditions. And two, even if farmers are rational, there are obvious reasons, such as the presence of risk and uncertainty, to suspect that they may not act to maximize profits. To the extent that farmers employ different technical practices than field experimenters and that farmers are not profit maximizers, our results can and generally will differ from those obtained via the analysis of field experiments. Our results, however, are directly comparable to other studies that have relied on actual field data, and what we have shown is that under the assumption of profit maximization, pest damage as it is usually measured in these studies systematically understates actual crop or revenue loss due to the presence and typically misstates actual economic damage caused by the presence of pests. Our empirical results suggest for our data set that more traditional measures of pest damage overstate actual losses incurred by farmers. Naturally, if this empirical result holds true for other studies, the perception of the significance of the pest problem could change markedly. And with that change could come significant changes in pesticide policies aimed at ameliorating the negative environmental externalities associated with the application of pesticides.

That leads to another caveat. The damages that we purport to measure are private damages suffered by individual farmers as a result of the presence of pests. There are two specific externalities that we have not addressed, but which will ultimately play an important role in the proper formulation of a scientifically sound pesticide policy. One is the environmental or health externality associated with the application of pesticides. Our measures are silent about this effect, and proper measurement of that effect is left to the other studies. The other emerges from the fact that pests can migrate across holdings of other farmers.[7] Thus, pesticide application on one plot can have potentially beneficial effects on damage to other farmers' crops. Our approach does not allow us to capture that effect, and to the extent that the effect is important, it suggests that our measures of the marginal productivity of pesticides may be biased.

9 References

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[7] We would like to thank the Associate Editor for raising this particular point.