Pesticide Productivity: Of Bugs and Biases

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Pesticide productivity is both important and difficult to measure. Typically, pesticide marginal products are estimated without information on the pest pressure. Three theoretical models are developed which suggest absence of such information may cause an underestimation of pesticide productivity. Using application frequency variables as a proxy for pest populations, we show that pesticide marginal products are higher when pest pressure is accounted for.

Key words: damage abatement, marginal product, pesticide economics, productivity, unobserved variables

Introduction

To protect public health, the government has aggressively pursued pesticide regulation through a series of laws beginning with the Federal Insecticide, Fungicide, and Rodenticide Act in 1947. Pesticide regulations have evolved such that today the only pesticides permitted are those which ensure "reasonable certainty that no harm will result from aggregate exposure to the pesticide chemical residues." This criterion makes the development and approval of new pesticides expensive, and has led to a 7% to 9% decrease in pesticide registration (Fernandez-Cornejo, Jones, and Smith).

A total ban on pesticide use in the United States has been estimated to cost $41 billion per year in higher food costs and lower quality crops and livestock (Knutson et al.). Thus, good pesticide policy clearly must consider the costs as well as the benefits of pesticide regulation. Economists often assess pesticide benefits by measuring pesticide marginal products. The higher the value of the pesticide marginal product relative to marginal cost, the greater the additional benefit from increasing pesticide use, and thus the greater the cost from more stringent regulation. If the value of the pesticide marginal product is low relative to marginal cost, it is more likely that farmers can profitably decrease pesticide use while simultaneously reducing environmental and health risks. It is clear, then, that regulatory mistakes can be made if pesticide marginal products are mis-measured. One source, among several, of mis-measurement is an inherent bias in the estimation of the marginal product due to choice of measurement procedure or data. This study examines analytically and empirically the bias due to omission of pest pressure in the estimation of pesticide marginal products.

Early attempts to measure the value of pesticide productivity found it to be quite high relative to pesticide marginal costs. Of the estimates conducted prior to 1986, 18 out of

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20 suggest an extra dollar spent on pesticides generates more than a dollar in return (Headley; Campbell; Fischer; Carlson), implying pesticides are systematically underused from a profit maximization point of view. In response, two possible sources of an upward bias in estimated marginal products have been put forth in the literature. First, almost all studies to date use cross-sectional data from private farms where data reflecting differences in land quality, managerial ability, and other fixed effects are not available (Campbell). If any of these fixed effects are correlated with pesticide use, then the corresponding marginal products may be biased. Carpentier and Weaver found, when fixed-firm effects are accounted for, marginal products are indeed lower.[1]

Second, all marginal product estimates before 1986 use the Cobb-Douglas production function. In a 1986 analysis, Lichtenberg and Zilberman argued that the single-equation, Cobb-Douglas model may be inappropriate, and offered a different model of the pesticide-yield relationship which might result in lower marginal products. This approach proposes a damage abatement model. Essentially, the approach considers the effect of pests on yield separately from the effect of pesticides on pests.

While some subsequent studies have found, under some circumstances, damage abatement models yield lower marginal products (e.g., Babcock, Lichtenberg, and Zilberman), others have reported higher estimates (e.g., Carrasco-Tauber and Moffitt). Finally, in an analysis using cross-sectional data from French farms, and accounting for fixed effects, Carpentier and Weaver concluded marginal products from both approaches are similar.

Although these earlier studies have provided rich insight into a potential upward bias in estimated pesticide marginal products, the potential for a downward bias has not been considered. Also, while unobserved fixed-firm effects have received much attention, a potentially more important unobserved effect is pest pressure. Pest pressure is arguably one of the most critical factors in explaining pesticide productivity. The data used in each of the studies cited above do not incorporate pest pressure measurements.

Pest pressure data have been used in many studies for purposes other than measuring pesticide productivity. For example, some have used pest pressure data to determine the threshold pest level warranting a single pesticide application (e.g., Gilmeister et al.; Marra and Carlson; Moffitt, Hall, and Osteen). These analyses utilize a competition function between pest numbers of a single pest and crop yield as an input into the calculation of the economic threshold pest population, but usually hold the pesticide's effects on pests to be a constant percentage kill ratio. Consequently, a measure of the *pest* marginal product is used, rather than a measure of the *pesticide* marginal product.

The present investigation suggests pesticide marginal products estimated in the absence of pest pressure information will probably be lower than the true marginal product. This study also demonstrates that pesticide marginal products estimated in the absence of pest populations are difficult to interpret. In the following section, the standard theoretical crop production function is used to explore, analytically, what pesticide marginal products represent when pest pressure is unobserved, and to illustrate the potential bias due to unobserved pest pressure.

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[1] This finding may be the result of differences in managerial ability, land quality, or other effects. If one farmer's soil tends to produce higher than average yields, the pesticide marginal product will be higher because there is more crop susceptible to damage, thereby eliciting higher pesticide usage. Here, the higher yield is falsely attributed to higher pesticide use, when the true source is better soil.

Estimates of pesticide marginal products with and without pest pressure information are then provided in the next section. Although pest numbers associated with each pesticide application are not available, information on the number of pesticide applications (denoted application frequency) is used as a proxy for pest pressure. Empirical estimates show that pesticide marginal products are higher with pest pressure variables than without. Both the theory and the empirical example in this study suggest pesticide marginal product estimates without pest pressure information will have a downward bias.

The Pesticide Marginal Product
When Pest Pressure Is Unobserved

In this section, a theoretical crop production function developed by Feder is used, which assumes there is only one period in the crop year for pests to inflict damage. This model is first analyzed assuming only that pest pressure and pesticides are positively correlated. Then, pesticides are assumed to be applied in a profit-maximizing manner. We then extend Feder's model to include multiple periods. The Feder model contains only one pest species and pesticide type.

Let yield (Y) in the absence of pest damage be given by a constant (Π), where this constant represents the contribution of fertilizers, rainfall, soil type, and similar inputs to yield. Yield damage from a single pest is assumed to be equal to $-\delta$, such that if Z is the pest population able to inflict damage and each pest's damage is independent of the total pest population, yield can be written as $Y = \Pi - \delta Z$.

Following Feder, pest damage can be prevented by the use of pesticides, where pesticide use is denoted by D. If $\psi(D)$ is the percentage of pests killed and an additive error ε is included, yield can be written as:

$$(1) \qquad Y = \Pi - \delta Z [1 - \psi(D)] + \varepsilon.$$

Feder assumes $\psi'(\cdot) > 0$ and $\psi''(\cdot) < 0$. The stochastic error ε is assumed to be independent of pesticide use and to have a zero mean. Note, the unobserved variable of concern is the *initial* pest density, not the pest density *after* the pesticide is applied—i.e., pest measures such as the average pest density will not solve the unobserved variable problem, as the average density is a combination of pests before and after pesticide applications.

The pesticide marginal product (hereafter denoted as PMP) is then described as follows:

$$(2) \qquad \frac{\partial Y}{\partial D} = \delta Z \frac{\partial \psi(D)}{\partial D}.$$

This PMP is increasing in pest pressure and the rate at which pests inflict damage. The PMP is positive but declining in pesticide use.

What does a PMP mean if it is not dependent on a measure of pest pressure? To address this question, we break the true production function in (1) into an observed and unobserved component by adding and subtracting an arbitrary constant $\bar{Z}$ to the true pest population:

$$(3) \qquad Y = \Pi - \delta \bar{Z} [1 - \psi(D)] + \left(-\delta [Z - \bar{Z}] [1 - \psi(D)] + \varepsilon\right),$$

where the first term is yield in the absence of pest damage, and the second term represents yield damage from an arbitrary pest population $\bar{Z}$ when D pesticides are applied. The third and fourth terms represent variations in yield due to unobserved pests and the error term. Since the first two terms are independent of pests, we can rewrite them as $\Pi - \delta\bar{Z}[1 - \psi(D)] \equiv \Pi + g(D, \beta)$, where β is a parameter vector. The function $g(D, \beta)$ represents yield loss if the true pest population equals $\bar{Z}$, and D pesticides are applied. This general function is intended to represent the types of functional forms estimated when pest pressure estimates are not available.[2] If pests are unobserved, the error term from the researcher's perspective is $v \equiv (-\delta[Z - \bar{Z}][1 - \psi(D)] + \varepsilon)$.

The value of $g(D, \beta)$ is ≤ 0, since pests cannot enhance yield by definition. Following Feder, we assume g_D, g_β, and $g_{D\beta} > 0$, and $g_{DD} < 0$. To reiterate, we are attempting to determine whether PMPs estimated in the absence of pests are unbiased estimates of true marginal products. Specifically, do they at least represent the true PMP at an arbitrary pest population? This will only be true if the parameter vector β can be estimated without bias. If $\hat{\beta}$ is larger than the true value, the estimated marginal product $g_D(\hat{\beta})$ will be larger than the true marginal product $g_D(\beta)$, since $g_{D\beta}$ is assumed greater than zero. For example, taking the PMP in (2), an increase in β is like an increase in pesticide effectiveness that increases the function $\partial\psi(D)/\partial D$, which increases the PMP.

If the estimate of β is obtained using least squares, the appendix shows the sign of $E(\hat{\beta} - \beta)$ equals the sign of:

$$(4) \qquad -\sum \delta[1 - \psi(D)] \frac{dZ}{dD} + \sum \delta[Z - \bar{Z}] \frac{\partial\psi(D)}{\partial D}.$$

If pesticide use is positively correlated with the pest pressure, as would seem the case, the first term is negative. The sign of the second term depends on the value of Z relative to $\bar{Z}$, but because $\bar{Z}$ is an unknown arbitrary constant and Z varies across observations, the sign of the second term is ambiguous. This suggests that when pest populations are unobserved, estimates of the parameter vector β making up the term $\Pi + g(D, \beta)$ are biased. Put differently, these PMPs have no clear interpretation. It is also unclear whether the PMPs are over- or underestimated. This can be explained intuitively. First, pests cause yield damage and are positively correlated with pesticide use. When pests are unobserved, the yield damage caused by higher pest numbers is falsely attributed to higher pesticide use, resulting in an underestimation of pesticide productivity.

Second, PMPs are increasing in the pest population. Higher pest numbers elicit both higher pesticide use and higher productivity at any usage level. This higher productivity is falsely attributed to higher pesticide use, and PMPs are overestimated. There are two forces biasing marginal product estimates, and they both work in opposite directions; therefore, it is unclear whether the overall bias is negative or positive. The next two model variants illustrate that while the sign of the bias remains ambiguous, there is evidence for hypothesizing a negative bias is more probable than a positive bias.

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[2] For example, Babcock, Lichtenberg, and Zilberman estimate a model where $Y = \Pi - \Pi Z \exp(\beta_0 - \beta_1 D)$. The marginal product is $\Pi Z \exp(\beta_0 - \beta_1 D)\beta_1$, and the derivative of the marginal product with respect to pesticide use is $-\Pi Z \exp(\beta_0 - \beta_1 D)\beta_1^2$. If β_1 is positive, the marginal product is positive but declining. This is similar to assuming $g_D > 0$ and $g_{DD} < 0$. Another example is the Cobb-Douglas model, where $Y = \Pi D^\beta$. Again, the marginal product is positive and declining so long as $0 < \beta < 1$. Also, with the Cobb-Douglas, we know an increase in β increases the marginal product, which is identical to assuming $g_{D\beta} > 0$.

The derivation of the bias considered previously does not account for how pesticides are applied on private farms, from which data are typically taken. We now present the bias differently, under the assumption pesticides are applied such that their marginal value product equals the marginal cost. A PMP represents yield damage prevented from a small change in pesticide use (D). Consider the ratio of yield differences to pesticide use differences below, where D and D' represent different pesticide levels. The ratio in (5) assumes a constant pest population:

$$(5) \qquad PMP \approx \frac{Y(D) - Y(D')}{D - D'} = \frac{-\delta Z[1 - \psi(D)] + \delta Z[1 - \psi(D')]}{D - D'} .$$

A [true] PMP is the limit of (5) as $D - D'$ goes to zero. Notice in (5), where the pest population across the two observations is constant, this yield difference will always be positive. To measure the true yield loss prevented from varying dosages of pesticide use, different pesticide amounts must be applied to a *similar pest population*. This condition usually is not met with data from private farms. If the private farms have identical technologies (their production functions are identical), are profit maximizers, face the same output and input prices, and the same transactions cost of applying pesticides, no two farms will ever apply different amounts of pesticides to the same pest population.

Suppose the above assumptions hold, but pest populations differ across farms. Let the output price be P and the marginal pesticide cost be r_D. Let D^i denote the profit-maximizing pesticide amount in response to pest population Z^i. Consider two farms, one with a pest population Z^1 and another experiencing Z^2, where $Z^1 > Z^2$. Under the previous assumptions, the average rate of change in yield with respect to pesticide use across both farms can be expressed as:[3]

$$(6) \qquad \frac{-\delta Z^1[1 - \psi(D^1)] + \delta Z^2[1 - \psi(D^2)]}{D^1 - D^2} >$$

$$\frac{r_D(D^1 - D^2)}{P(D^1 - D^2)} + \frac{-\delta Z^1[1 - \psi(D^2)] + \delta Z^2[1 - \psi(D^2)]}{D^1 - D^2} .$$

The first term in (6) is similar to how PMPs are measured across farms when pest pressure is unobserved. If $Z^1 > Z^2$, then $D^1 > D^2$, since the PMP is increasing in pest pressure. This implies the first term on the right-hand side is positive, but the second term is negative. The sign of (6) is ambiguous. If $Y(D)$ were deterministic, such that a regression was being estimated on data containing no stochastic components, one could easily plot the true production function. If pests are unobserved and one plots points of the deterministic function $Y(D)$, with yield on the y-axis and pesticides on the x-axis, a downward-sloping production function may result. Adding a stochastic component does not eliminate this possibility. The plotted function would not pertain to the true relationship between yield and pesticides holding all else constant, but would only represent yield and pesticide points, as *both* pesticides and pests vary. If pests could be held constant, the plot of points would definitely reveal an upward-sloping curve (up to the third stage of production).

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[3] By definition of profit maximization, $\Pi - \delta Z^1[1 - \psi(D^1)] - r_D D^1/P > \Pi - \delta Z^1[1 - \psi(D^2)] - r_D D^2/P$. If we add and subtract $\Pi - \delta Z^2[1 - \psi(D^2)] - r_D D^2$ to each side and rearrange terms, the expression in (6) is obtained.

The first model variant only illustrates the existence of a bias, where a positive bias is as likely as a negative bias. This second model variant shows the possibility of estimating negative marginal products when the true marginal product is positive, implying a negative bias in the estimated marginal product. We suspect a negative bias is more likely than a positive bias. However, we acknowledge it is not a proof.

So far, only the potential bias in a one-period setting has been considered. In reality, crops may experience multiple pest infestations which require multiple pesticide applications. In this setting, there is more than one definition of "pesticide use." It could mean a single pesticide dosage or the sum of all pesticide dosages. Most studies utilize the latter. Some studies define pesticide use as total yearly pesticide expenditures (Headley; Fischer; Chambers and Lichtenberg; Teague and Brorsen; Carlson; Carrasco-Tauber and Moffitt; Campbell), while others use total pounds of active ingredients applied throughout the crop year (Babcock, Lichtenberg, and Zilberman), and others use some other form of total pesticide application throughout the crop year (Saha, Shumway, and Havenner; Carpentier and Weaver).

Differences in total seasonal pesticide use across observations could be attributed to a different number of equal pesticide applications, a different amount of pesticides applied at each application, or both. This makes interpreting PMPs difficult. After modifying the crop production function in (1) to allow two time periods, we obtain:

$$(7) \qquad Y = \Pi - \delta Z_1\big[1 - \psi(D_1)\big] - \delta Z_2\big[1 - \psi(D_2)\big] + \varepsilon,$$

where Z_i and D_i are the pest and pesticide application levels, respectively, in period i. Consider two farms where the pest populations are equal in the first period. In response, both farms apply an equal pesticide dosage D_1^*. Further, suppose the pest population for one farm is positive in the second period, but zero for the other farm. This could be due to farm-specific effects such as different weather conditions which may affect pest mobility or pesticide effectiveness, or to differences in skill levels in pesticide application. In the second time period, one farmer does not apply any pesticide while the other applies D_2^*. The average rate of change in yield with respect to pesticide use between each farm is then specified as:[4]

$$(8) \qquad \frac{-\delta Z_2[1 - \psi(D_2^*)]}{D_2^*}.$$

This term is negative, implying the estimated PMP will always be negative, even though the second pesticide application may have prevented a large yield loss. The fact that crops can experience numerous intra-seasonal pest infestations provides considerable justification for estimating negative PMPs.

The models described above establish that PMP estimates are biased when pests are unobserved. Although no proof can be given, several of the models' implications suggest an underestimation of pesticide productivity. The first model simply shows a bias exists. The second model demonstrates that estimated PMPs can be negative when the true PMP is positive, which would imply a "large" negative bias. We argue this makes a

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[4] One farm applies D_1^*, while the other applies $D_2^* + D_1^*$. The difference equals D_2^*. Yield on one farm is $\Pi - \delta Z_1[1 - \psi(D_1^*)]$, and on the other farm is $\Pi - \delta Z_1[1 - \psi(D_1^*)] - \delta Z_2[1 - \psi(D_2^*)]$. Hence, the average rate of change in yield with respect to pesticide use is $\{\Pi - \delta Z_1[1 - \psi(D_1^*)] - \delta Z_2[1 - \psi(D_2^*)] - \Pi + \delta Z_1[1 - \psi(D_1^*)]\}/\{D_2^* + D_1^* - D_1^*\} = \{-\delta Z_2[1 - \psi(D_2^*)]\}/\{D_2^*\}$.

negative bias more probable, but again this is not a proof. Finally, the third model presents a setting where estimated PMPs will always be negative when the true PMP is positive. Since this setting is representative of many farms, the third model also makes a negative bias more likely.

Still, the sign and significance of the bias remains an empirical issue. In some cases, although data are not available on the total pest population within a crop year, data are available on the number of applications in a year. Because a higher total pest population will elicit a greater number of applications, application frequency is a useful instrument for the total pest population. Estimating PMPs with and without application frequency variables is then useful for determining the sign and magnitude of the estimation bias. Although multicollinearity will exist between application frequencies and pesticide applications, multicollinearity would exist even if the true pest numbers were used. To better identify the sign and magnitude of this bias, the next section presents empirical estimates of PMPs with and without application frequency variables.

Empirical Pesticide Marginal Product Estimates
With and Without Pest Pressure Information

In the previous section, the bias due to unobserved pest pressure data was illustrated. When there is only one pest infestation each year, the bias is ambiguous. If there are multiple, equal pest infestations within a crop year, the bias must be negative, because pesticide marginal products (PMPs) will always be [estimated as] negative despite the fact that pesticides prevented yield damage. In reality, there are multiple, unequal pest infestations within a crop year. Thus, while the theoretical models *suggest* a downward bias, the sign and magnitude of the bias remain an empirical issue.

This section utilizes empirical data to help resolve this ambiguity. Insecticide marginal products are estimated using potato production data. These data are useful because, coming from an experimental setting, they do not have unobserved fixed-firm effects. Another desirable feature is that the experiments mimic how insecticides are used on profit-maximizing farms. The most appealing feature of these data is that the number of insecticide applications made each year per observation is known.[5] The number of insecticide applications is an indicator of insect pressure. By estimating PMPs with and without application frequency variables, the effect of unobserved insect pressure on PMPs can be measured.

Potato production data were collected from a University of Maine potato research station in Presque Isle, Maine. The main objective of the experiment was to estimate the difference in profitability when certain inputs (e.g., pesticides or synthetic fertilizer) are reduced from their normal levels. From 1991–1995, a total of 96 plots were managed on one contiguous plot of land. Each plot was 15% of an acre, and was rotated with a cover crop, giving 143 total observations of yields and input use over the five-year period. Yield (Y) varied over the range (9, 60) cwt per plot, with an average of 42 cwt per plot.

Half of the plots were planted in the Atlantic variety and the other half in the Superior variety; this effect is captured by a dummy variable for the Superior variety (S) in our

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[5] Herbicides and fungicides were also applied. Herbicides were not applied in response to pest pressure information on all the plots, and fungicides were applied according to a preplanned strategy. For these reasons, herbicide and fungicide variables are not included in the analysis.

empirical example. All plots received synthetic fertilizer treatments, while half the plots received less fertilizer and an extra treatment of compost and manure, identical in nutrient composition. These effects were captured by a continuous fertilizer use variable (F) and a dummy variable for those plots receiving compost and manure (amended plots, or A). Rainfall, measured in inches per year from a nearby weather station, was also included as an explanatory variable (R). Rainfall varied from 34 to 40 inches per year.

In response to insect pests such as the Colorado potato beetle and green peach aphids, five insecticide types were applied. Due to degrees of freedom issues, each insecticide type was converted to pounds of active ingredient to produce one insecticide variable (D) detailing the total amount applied per plot throughout the crop year. The conversion of insecticides to pounds of active ingredients made their values small and spread over a small range (0.08 to 0.58 pounds per plot per year). To make the insecticide marginal product easier to interpret, the PMPs were converted to represent the per acre increase in yield from increasing insecticide use by 1%.[6] Additional descriptive statistics are given in table 1.

These data allow estimating yield as a function of the inputs described above, in a manner which displays no unobserved fixed-firm effects. Insect population measures, however, are not available. At some time these population numbers preceding applications would have been known, since the applications are based on economic thresholds. The only direct pest population data recorded, however, were the within-season geometric mean populations for each plot. These mean populations refer to insect populations before and after pesticide treatment, and therefore are not useful for estimated PMPs. Since the number of insecticide applications was recorded, and this number is positively correlated with total initial insect infestations, application frequency numbers are an acceptable proxy for insect pressure measurements.

About half of the plots received insecticide applications at the economic threshold and dosage used by private farmers. The economic threshold in this study is a pest level at which the marginal benefit of a particular dosage of pesticide just equals its marginal cost. These thresholds were developed by agricultural economists so as to ensure profit maximization as the objective. Because private farms follow these suggested thresholds and dosages in Northern Maine, these observations are reflective of farmer behavior in the study area.

The remaining plots only received insecticides when insects exceeded twice the economic threshold number, resulting in lower insecticide use than would normally be observed on commercial farms. The insecticide dosage was also reduced. This approach allows estimating PMPs at current levels versus lower levels of insecticide use (when higher thresholds and lower dosages are employed).

The two most common production functions are the damage abatement function and the Cobb-Douglas function. Since there is no consensus as to which is best, we estimate both. The most common damage abatement function is the exponential function (Babcock,

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[6] A marginal product can be interpreted as a first-order approximation to the increase in yield from increasing an input by one unit. Insecticide use in these data never increases by one, but by much smaller values, making the marginal products seem very large. To facilitate interpretation, all marginal products are multiplied by a constant. This constant is 1% of average insecticide use (0.36 pounds active insecticide ingredients per plot per year) divided by 0.15 (to convert it to a per acre basis), or $(0.01)(0.36)(0.15)^{-1} = 0.024$. Thus, the marginal product can be interpreted as the first-order approximation to the yield change if insecticide use increases by 0.024 (1% of the average) per acre. Otherwise, it is possible for estimated marginal products to exceed yield, making interpretation difficult. This transformation does not influence the sign or significance of the marginal product; it only makes it easier to interpret.

Table 1. Maine Potato Production, Descriptive Statistics (143 observations, 1991–1995)

Variable	Unit	Mean (Std. Dev.)
Yield (Y)	cwt/plot	42 (11)
Fertilizer (F)	lbs./plot	132 (51)
Rainfall (R)	inches/year	37 (2)
Superior variety (S)	number of plots	71
Plots receiving identical treatments of compost and manure (amended plots, or A)	number of plots	72
Insecticides (D)	lbs. active ingredient/plot	0.36 (0.15)
Number of insecticide applications (N)	number/plot	3.66 (1.80

Note: One plot is 15% of an acre.

Lichtenberg, and Zilberman; Carpentier and Weaver; Carrasco-Tauber and Moffitt) whose form is given in the literature as follows:[7]

$$(9) \qquad Y = \prod_i X_i^{\alpha_i} \left[1 - \exp(\gamma_0 - \gamma_1 D) \right] + \varepsilon,$$

where Y is yield, X_i is the ith productive (non-damage abating) input (e.g., fertilizer), and D is a damage abating input (e.g., insecticides). The Cobb-Douglas function is specified as:

$$(10) \qquad Y = \prod_i X_i^{\alpha_i} D^{\gamma_1} e^{\varepsilon},$$

where ε is a stochastic error term. The term $\prod_i X_i^{\alpha_i}$ is often referred to as the potential yield function, which describes yield if there is no pest pressure, and thus no insecticides are applied. This function is identical for both models. Yield (Y) in cwt per plot in the absence of pests is defined to be a function of a dummy variable for amended plots (A), a dummy variable for the Superior variety (S), fertilizer in pounds per plot (F), and rainfall in inches per plot per year (R), shown as follows:

$$(11) \qquad \text{If no pests,} \quad Y = \prod_i X_i^{\alpha_i} = \exp\left(\alpha_0 + A\alpha_1 + S\alpha_2 \right) F^{\alpha_3} R^{\alpha_4}.$$

The two models then differ in how insecticides (D) enter the production function.

Neither model in (9) or (10) contains pest pressure variables. Pest population information is included here by using application frequency variables. Recall insecticides were

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[7] The Cobb-Douglas model expresses yield (Y) as $Y = A^a D^\beta$, where D is pesticides and A is other inputs. A restricted version of the original damage abatement function replaces D with $h(D)$, where $h(D)$ lies on the $(0, 1)$ interval. The function $h(D)$ contains parameters which must be estimated. Lichtenberg and Zilberman argued that if the true function is $Y = A^a [h(D)]^\beta$, but researchers instead estimate $Y = A^a D^\beta$, they will underestimate the pesticide marginal product. In a more recent study, Hall and Moffitt show the sign of the bias is theoretically ambiguous. The exponential damage abatement function expresses $h(D)$ as $[1 - \exp(\gamma_0 - \gamma_1 D)]$ and sets $\beta = 1$.

applied on some plots when insect numbers cross the economic threshold (as private farmers would), while other plots apply insecticides at a higher threshold to identify the effect on output and profit of reduced insecticide use. The first plots are referred to as "typical plots," while the latter are referred to as "reduced use plots." Thus, for an identical series of pest infestations, more applications are expected to be given to the typical plots than to the reduced use plots. This implies the coefficients on application frequency variables should differ depending on whether the observation is a typical plot or a reduced input plot.

Let N be the number of insecticide applications per plot per year, and RUP be a dummy variable equaling one if the plot is a reduced use plot. Application frequency variables are incorporated into the damage abatement function as follows:

$$(12) \qquad Y = \left[\exp(\alpha_0 + A\alpha_1 + S\alpha_2)F^{\alpha_3}R^{\alpha_4} \right]\left[1 - \exp(\gamma_0 - \gamma_1 D) \right]\left[N^{\beta_1 + \beta_2 RUP} \right] + \varepsilon.$$

Similarly, the Cobb-Douglas is specified as:

$$(13) \qquad Y = \left[\exp(\alpha_0 + A\alpha_1 + S\alpha_2)F^{\alpha_3}R^{\alpha_4} \right]\left[D^{\gamma_1} \right]\left[N^{\beta_1 + \beta_2 RUP} \right] + \varepsilon.$$

This modification inserts pest information consistent with Moffitt, Hall, and Osteen. Both models are estimated with and without application frequency variables to determine how PMPs differ when pest pressure information is not used.

The parameter estimates for both models are reported in tables 2 and 3.[8] Since the production functions are highly nonlinear, making Wald tests undesirable, all standard errors are calculated using 100 nonparametric bootstraps (Dagenis and Dufour). In general, amended plots and plots planted in the Superior variety have lower yields. The marginal product with respect to fertilizer is negative, suggesting fertilizer is overapplied. The coefficients suggest rainfall is the major yield determinant.

Insecticide marginal products are calculated for both models in table 4. Nonparametric bootstraps, where the original observations are sampled with replacement 100 times, are used to calculate the mean and standard deviation of each model's estimated PMP, with and without pest information. At each bootstrap, all non-insecticide variables are left at their original values. This provides 143 marginal products, one for each observation. The average of the 143 marginal products is then used as the point estimate for that bootstrap. The marginal product is defined as the change in expected yield with respect to pesticide use. But to facilitate interpretation, this marginal product is multiplied by {0.01 * mean pesticide use}, because the pounds of active ingredient is a small number and never increases by one. It is then divided by 0.15 to convert marginal products from a per plot to a per acre basis. With this transformation, the marginal product is a first-order approximation to the yield increase from a small increase (0.01 * mean pesticide use) in per acre pesticide use.

At each bootstrap, the PMP from each model was observed to determine whether it was greater than zero. The percentage of bootstraps where the PMP was greater than zero can be interpreted as one minus the p-value for the null hypothesis that the PMP

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[8] Note that one cannot use the coefficient estimate and standard error from pesticide parameters in these two production functions to assess the significance of pesticide marginal products. Even if the pesticide parameter is insignificant, the pesticide marginal product may be highly significant. This is because pesticide marginal products are a nonlinear function of all model parameters.

Table 2. Estimates from Damage Abatement Production Function

Parameter	Parameter Estimates (Std. Errors in Parentheses)	
	Without Application Frequency Variable	With Application Frequency Variable
α_0 (constant)	6.9849* (0.0393)	7.1258* (0.8989)
α_1 (A = amended plots)	-0.1030* (0.0348)	-0.1064* (0.0384)
α_2 (S = Superior variety)	-0.5941* (0.1228)	-0.2137 (0.1220)
α_3 (F = fertilizer)	-0.8679* (0.1511)	-0.3677* (0.1582)
α_4 (R = rainfall)	2.3610* (0.3902)	0.9210* (0.4503)
γ_0 (constant)	-0.0007 (0.0022)	-0.0106 (0.0350)
γ_1 (D = insecticides)	0.0001 (0.0004)	0.0663 (0.1924)
β_1 (N = number of insecticide applications)	—	-0.9523* (0.1530)
β_2 (RUP = dummy variable for reduced use plots)	—	0.0179 (0.0328)
Coefficient of Determination	0.52	0.59

Notes: An asterisk (*) denotes statistical significance at the 5% level. Standard errors are calculated via nonparametric bootstraps by sampling the original observations with replacement 100 times. Estimation is achieved using nonlinear least squares.

Table 3. Estimates from Cobb-Douglas Production Function

Parameter	Parameter Estimates (Std. Errors in Parentheses)	
	Without Application Frequency Variable	With Application Frequency Variable
α_1 (constant)	-0.8370 (1.4322)	4.3930* (2.0893)
α_2 (A = amended plots)	-0.4726* (0.0831)	0.1187 (0.1939)
α_3 (S = Superior variety)	-0.1253* (0.0444)	-0.1259* (0.0402)
α_4 (F = fertilizer)	-0.7761* (0.1283)	0.0281 (0.2571)
α_5 (R = rainfall)	2.3697* (0.4002)	0.4714 (0.6603)
γ_1 (D = insecticides)	-0.0083 (0.0309)	0.6849* (0.2339)
β_1 (N = number of insecticide applications)	—	-1.1888* (0.3789)
β_2 (RUP = dummy variable for reduced use plots)	—	-0.0070 (0.0283)
Coefficient of Determination	0.47	0.50

Refer to notes to table 2 above.

Table 4. Estimated Insecticide Marginal Products (observed at average per acre insecticide use)

Description	DAMAGE ABATEMENT MODEL		COBB-DOUGLAS MODEL	
	Without Application Frequency Variable	With Application Frequency Variable	Without Application Frequency Variable	With Application Frequency Variable
Average marginal product	0.0867	2.1913	-0.0167	2.5833
Standard deviation of marginal product	(0.1113)	(0.3553)	(0.0880)	(1.0740)
% of times marginal product is positive in bootstraps	83%	100%	40%	100%

from each model is equal to zero. The alternative hypothesis is that the PMP is greater than zero. One would reject the null hypothesis in favor of the alternative hypothesis at the 5% confidence level if the percentage of positive bootstraps is greater than 95%.

For the damage abatement model, the PMP is larger when an application frequency variable is included (table 4). In the Cobb-Douglas model, the PMP is not significantly different from zero without an application frequency variable, but with the frequency variable it is significant and positive. Note, when the application frequency variable is excluded, the estimated marginal product is lower for the Cobb-Douglas model compared to the damage abatement model. Lichtenberg and Zilberman argued that the damage abatement function should provide lower PMPs than the Cobb-Douglas, and showed this is the case only if the damage abatement function is the true model.

Thus, as Carpentier and Weaver point out, Lichtenberg and Zilberman hypothesize that PMPs are lower with damage abatement functions, but do not prove it. Since the true functional form is unknown, PMPs can be lower or higher with damage abatement functions than the Cobb-Douglas. Carrasco-Tauber and Moffit demonstrate that while damage abatement functions sometimes do yield lower marginal products, in other cases they are higher.

These estimates suggest, at least in this case, estimated pesticide marginal products are lower without pest pressure information. To further test the hypothesis that PMPs will be underestimated if pest pressure variables are not included, a statistical test is conducted. A series of 100 nonparametric bootstraps are performed, where the original observations are randomly sampled with replacement. At each bootstrap, the insecticide marginal product at mean insecticide use is calculated for each model with and without application frequency variables. For each of the models, the percentage of times the PMP with application frequency variables is less than the PMP without application frequency variables is calculated for all 100 bootstraps. This percentage can be interpreted as the p-value for the null hypothesis that the average PMP is equal with and without pest pressure information, versus the alternative hypothesis that the average PMP is higher when pest pressure information is used.

The p-value was 0% for both models, implying the PMP with pest pressure variables was higher than the PMP without pest pressure variables 100% of the time. These results suggest pesticide productivity estimates are lower when pest pressure information is ignored. Recall, Carpentier and Weaver found that unobserved firm and time effects may lead to an overestimation of productivity, even in a damage abatement

framework. Whether the exclusion of both types of unobserved variables will offset each other in part or in whole in a particular application is an empirical question.[9]

Summary and Implications

Pesticide marginal product measurements are necessary for establishing good farm and food policy. Measuring pesticide productivity is both critical and difficult. Agricultural economists never have perfect data, nor is obtaining perfect data worth the cost. Thus, we make measurements to the best of our ability, and continually monitor the extent to which our estimates are biased. Historically, studies have focused on factors which tend to overestimate pesticide productivity. These include model misspecification and unobserved fixed-firm effects. This study focuses on an unobserved variable, pest pressure, that may cause pesticide productivity to be underestimated.

From a theoretical perspective, we cannot prove unobserved pest pressure causes an underestimation of pesticide productivity. However, three illustrations here suggest an underestimation. Data on Maine potato production are employed to test the resulting hypothesis that pesticide productivity can be underestimated.

Two standard approaches are used to measure insecticide marginal products. To evaluate how these marginal products change when pest pressure information is included, marginal products are estimated with and without insecticide application frequency variables. Hypothesis tests imply PMPs are significantly higher with pest pressure information than without. We argue that pesticide productivity estimates without the inclusion of pest pressure information will likely underestimate the true pesticide productivity (ceteris paribus). We therefore conclude that pesticide marginal products measured with pest pressure information omitted can lead to policies with greater costs than expected.

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[9] We thank an anonymous reviewer for pointing this out.

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Appendix:
Illustration of Function $g(D, \beta)$
When the Pest Population Z Is Unobserved

Suppose the true production function is $Y = \Pi - \delta Z [1 - \psi(D)] + \varepsilon$. This analysis shows this function can be written as $Y = \Pi - \delta \bar{Z} [1 - \psi(D)] + (-\delta [Z - \bar{Z}] [1 - \psi(D)] + \varepsilon)$, which by definition equals $Y = \Pi + g(D, \beta) + (-\delta [Z - \bar{Z}] [1 - \psi(D)] + \varepsilon) = \Pi + g(D, \beta) + v$. The purpose of this appendix is to illustrate what happens if we estimate the function $g(D, \beta)$ when the pest population Z is unobserved. It is assumed that Π is known or can at least be estimated without bias.

The derivative g_β represents the true marginal product at the arbitrary pest population $\bar{Z}$. If the parameter vector β can be estimated without a bias, then the estimate of g_β is meaningful; it represents the true marginal product at an arbitrary pest population. Otherwise, the estimated marginal product has no good interpretation. Assuming the parameter vector β is estimated using least squares, its estimate must satisfy the following:

(A1)
$$\min_{\hat{\beta}} \sum \left(Y - \Pi - g(D, \hat{\beta})\right)^2 = \min_{\hat{\beta}} \sum \left(v(\hat{\beta})\right)^2$$

or

(A2)
$$(-2) \sum v(\hat{\beta}) g_{\hat{\beta}} = 0.$$

Using (A2) and the mean-value theorem, the term $\hat{\beta} - \beta$ can be written as:

(A3)
$$\hat{\beta} - \beta = -\left[\sum \frac{\partial \{v(\hat{\beta}) g_{\hat{\beta}}\}}{\partial \bar{\beta}}\right]^{-1} \sum \left(-\delta [Z - \bar{Z}][1 - \psi(D)] - E\{-\delta [Z - \bar{Z}][1 - \psi(D)]\} + \varepsilon\right) g_\beta$$

or

(A4)
$$\hat{\beta} - \beta = -\left[\sum \frac{\partial \{v(\hat{\beta}) g_{\hat{\beta}}\}}{\partial \bar{\beta}}\right]^{-1} \sum \left(v(\beta)\right) g_\beta,$$

where $\bar{\beta} = \lambda\hat{\beta} - (1 - \lambda)\beta$ for $0 \le \lambda \le 1$. The term in (A3) assumes that an intercept in $g(D, \beta)$ is used to capture the unconditional expectation of $-\delta[Z - \bar{Z}][1 - \psi(D)]$.

For the estimate of β to be unique, it must be that

$$\sum \frac{\partial\{v(\bar{\beta})g_{\bar{\beta}}\}}{\partial\bar{\beta}}$$

is a positive definite matrix, which implies its inverse is as well. We wish to know the sign of the expected value of $\hat{\beta} - \beta$. If the values of v and g_β are assumed independent across observations, the expected value of vg_β equals $E(v)E(g) + cov(v, g)$. Since the expected value of ε and $[-\delta[Z - \bar{Z}][1 - \psi(D)]$ $- E\{-\delta[Z - \bar{Z}][1 - \psi(D)]\}]$ is zero, the sign of this expectation simply equals the sign of the covariance of v and g_β. Both g_β and $g_{\beta D} = g_{D\beta}$ are assumed to be positive, so if the term v is increasing in D, this covariance is positive. If v is decreasing in D, the covariance is negative. Noting the following derivative,

(A5)
$$\frac{\partial - \sum\left(\delta[Z - \bar{Z}][1 - \psi(D)] - E\{\delta[Z - \bar{Z}][1 - \psi(D)]\} + \varepsilon\right)}{\partial D}$$

$$= -\sum \delta[1 - \psi(D)]\frac{dZ}{dD} + \sum \delta[Z - \bar{Z}]\frac{\partial\psi(D)}{\partial D},$$

it can be seen that the sign between v and g_β for each observation is uncertain. If the covariance between pests and pesticides is positive, as would seem the case, the first term is negative. However, the sign of the second term depends on the value of Z relative to $\bar{Z}$. But since $\bar{Z}$ is an arbitrary constant and Z varies across observations, the sign of the second term is ambiguous. This implies the sign of the expected value of $\hat{\beta} - \beta$ is unknown, and is not necessarily zero. Since it is not zero, the estimate $\hat{\beta}$ is biased, where the direction of the bias is unknown.