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Does It Matter Who Scouts?

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Scouting is the most widely used integrated pest management technique adopted by U.S. growers. This study applies an implicit demand formulation of the Lichtenberg-Zilberman damage abatement model to data from a survey of Maryland field crop growers to examine differences in pesticide demand between growers using scouts trained and supervised by extension and those using chemical dealer employees or scouting themselves. The results give partial support to those skeptical of the quality of scouting by farmers themselves and by consultants working for chemical dealers. Soybean growers using extension-trained scouts had significantly lower pesticide demand than those using chemical dealer employees or scouting themselves. However, no significant differences were found in the pesticide demands for alfalfa, corn, and small grains.

Key words: crop loss, damage abatement, extension, integrated pest management, pesticide demand, pesticides, scouting

Introduction

Integrated pest management (IPM) is an approach that combines the use of chemical pesticides with nonchemical methods to limit the damage caused by such pests as insects, weeds, diseases, and rodents. Among the nonchemical techniques used in IPM strategies are protection of natural pest enemies, cultivation practices that limit pest overwintering or diffusion, and crop rotation [for a review, see Kogan (1998)]. The most widely used nonchemical method is scouting—i.e., monitoring fields to determine actual pest infestation levels. In scouting-based IPM strategies, chemical pesticides are applied only when the pest infestation level exceeds the economic threshold, usually defined as the level at which the value of crop losses will exceed the costs of pesticide application [see Pedigo, Hutchins, and Higley (1986) for a standard exposition].

Pest management regimes based on scouting and economic thresholds have largely replaced the earlier practices of spraying preventively on a predetermined calendar-based schedule. By the early 1990s, according to the U.S. Department of Agriculture (USDA), scouting was used on 78% of U.S. corn acreage, 77% of U.S. soybean acreage, 80% of U.S. wheat acreage, 86% of U.S. potato acreage, 88% of U.S. cotton acreage, 76%

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of U.S. fruit and nut acreage, and 71% of U.S. vegetable acreage (USDA/Economic Research Service, 1997; Vandeman et al., 1994).

Despite its apparent widespread adoption, certain aspects of scouting remain somewhat controversial. One bone of contention is the issue of who performs scouting and makes spray recommendations. Scouting is performed by independent crop consultants, by consultants working as employees of farm chemical sales firms, or by farmers themselves. Some believe that only independent crop consultants provide unbiased scouting information [see, for example, Zilberman et al. (1994) for a discussion of this debate]. Those who hold this point of view argue that farmers tend to overestimate pest infestation levels due to lack of training and risk aversion [see Pingali and Carlson (1985) for some evidence confirming this hypothesis for apple growers in North Carolina, albeit at a much earlier point in the diffusion of scouting]. They also argue that consultants working for farm chemical dealers overstate infestation levels, use excessively low economic thresholds, or both, in order to increase pesticide sales. Since the majority of scouting is done by farmers and chemical dealer employees, proponents of this perspective posit that scouting may not be a very effective means of reducing chemical pesticide application.

As a counterargument, it has been suggested that consultants working for chemical dealers can be impelled to generate unbiased scouting reports and spray recommendations in order to retain customer loyalty by competition from independent crop consultants, from other dealers, and from farmers with sufficient human capital to scout accurately and apply economic thresholds themselves (Zilberman et al., 1994). It is also possible that extension dissemination efforts create widespread familiarity with scientific scouting methods and economic thresholds, enabling growers to employ economic thresholds based on their own scouting and to make accurate assessments of scouting reports and spray recommendations generated by consultants in the employ of chemical dealers. As a result, it may not matter who scouts: Independent consultants, consultants working for chemical dealers, and farmers who scout themselves may generate the same spray recommendations so that scouting, regardless of who performs it, will affect pesticide demand in a consistent manner.

There are few empirical studies examining the impacts of scouting on pesticide demand, and none examining differences between the effects of scouting by extension-trained consultants and scouting by farmers or chemical dealer employees. Most of the existing empirical studies compare the average amounts of pesticides applied by farmers participating in an IPM demonstration project with the average amounts applied by nonparticipants [for a survey, see Norton and Mullen (1994)]. Comparisons of this kind are not highly satisfactory because they do not control for differences in land quality, human capital, input and output prices, pest pressure, and other factors that can influence pesticide use.

Econometric studies, which do control for such variations, tend to show that scouting reduces pesticide use. Burrows (1983) found that participation in an IPM program featuring scouting reduced expenditures on pesticides significantly among California cotton growers during the early 1970s. Pingali and Carlson (1985) reported scouting reduced North Carolina apple growers' demand for insecticides and fungicides during the late 1970s by reducing errors in their assessments of insect and disease pressure. More recently, Hubbell and Carlson (1998) found that apple growers using scouting selected different insecticides than those who did not use scouting, but found no difference in the total weight of insecticidal chemical active ingredients applied or in the potential harmfulness of the chemicals used in terms of human safety or the environment. Hubbell (1997) found some weak evidence suggesting scouting may influence the frequency with which apple growers apply insecticides. Fernandez-Cornejo (1996) found that tomato growers using insect scouting plus one or more other nonchemical pest control methods made a smaller number of insecticide applications than those who did not.

This paper uses data on Maryland field crops to compare the pesticide demands of growers using scouting by extension-supervised independent crop consultants with those who did not; most of the latter used scouting, but either scouted themselves or had scouting performed by chemical dealer employees. Maximum-likelihood estimators are formulated for implicit demand functions derived from the damage control specification introduced by Lichtenberg and Zilberman (1986), an approach to estimating damage abatement parameters that has not been used previously. We use those estimators to test for differences in pesticide demand between farmers obtaining scouting services from consultants trained and certified by Maryland Cooperative Extension (MCE) and those who did not in terms of both the parameters of damage abatement functions and the variances of random errors affecting production. Finally, these estimated parameters provide the focus for a discussion of pesticide productivity on Maryland field crops.

A Model of Pesticide Demand

We follow Lichtenberg and Zilberman (1986) in modeling pest management services as an intermediate input providing damage control. Lichtenberg and Zilberman motivated this approach on the grounds of a priori biological information, noting that pest management methods generally do not augment plant growth, but rather reduce crop loss due to pests. They also argued that generic first-order functional forms are likely to overstate the productivity of pest management, so that pesticides appear to be underused in cases where they are actually overused. As Chambers and Lichtenberg (1994) subsequently pointed out, an additional advantage of the damage-control approach is that it generates implicit estimates of percentage crop loss and thus puts pesticide productivity in terms better understood by crop scientists.

Several empirical applications have found that this damage-control approach yielded better-fitting or more plausible estimates of pesticide productivity for North Carolina apples (Babcock, Lichtenberg, and Zilberman, 1992), Kansas wheat (Saha, Shumway, and Havenner, 1997), and U.S. aggregate agricultural output (Chambers and Lichtenberg, 1994). In contrast, other studies of aggregate U.S. agricultural output (Carrasco-Tauber and Moffitt, 1992) and aggregate French cereal and oilseed production (Carpentier and Weaver, 1997) concluded that damage-control models fit no better (but also no worse) than generic specifications. In a recent study by Norwood and Marra (2003), both damage-control and Cobb-Douglas models were used to explore the effects of including measures of pest pressure on estimates of pesticide productivity in Maine potatoes. However, they did not compare the relative fit of the two models.

Like these other studies, we specify output Q as a weakly separable combination of potential yield $F(\mathbf{X})$ and damage abatement $G(Z, \alpha)$, where $\mathbf{X}$ is a vector of normal inputs, Z denotes pest control inputs (specifically, the amount of pesticides applied), α

is a vector of parameters, and damage abatement is scaled to lie in the unit interval.[1] If pesticides are essential [in the technical sense that production is physically impossible without them—i.e., where $G(0, \alpha) = 0$—crop loss is total when pesticides are not used], then zero is the minimum possible value for abatement. If pesticides are not essential inputs, as most crop scientists believe, then the minimum possible value of $G(Z, \alpha)$ is positive.

Because the number of observations on each crop is small, parsimony in parameters is critical. To this end, we employ the implicit demand specification suggested by Chambers and Lichtenberg (1994). Output of farmer j is given by:

$$Q_j = F(\mathbf{X}_j)G(Z_j, \alpha)u_j, \tag{1}$$

where u_j is a lognormal white noise error consisting of random variations in unobserved factors affecting both potential yield and damage abatement (e.g., human capital, pest pressure, microclimatic variations in weather, etc.), assumed to be distributed independently and identically across farms. Profit is denoted by:

$$\pi(\mathbf{X}_j, Z_j, \alpha) = pF(\mathbf{X}_j)G(Z_j, \alpha)u_j - \mathbf{w} * \mathbf{X}_j - vZ_j, \tag{2}$$

where p is the crop price, $\mathbf{w}$ is a vector of the unit prices of normal inputs, and v is the unit price of pesticides. The first-order condition for the farmer's profit-maximizing pesticide use selection Z_j can be written as:

$$\ln\left(\frac{v}{R_j}\right) - \ln\left(\frac{G'(Z_j, \alpha)}{G(Z_j, \alpha)}\right) = \ln(u_j), \tag{3}$$

where $R_j = pF(\mathbf{X}_j)G(Z_j, \alpha)$ is farmer j's expected revenue. If R_j and v are observed, only the parameters of the damage abatement function α need be estimated.

Neither theory nor empirical studies give guidance as to the exact specification of $G(Z, \alpha)$, other than it have the attributes of a cumulative distribution function. Consistent with earlier empirical studies (Babcock, Lichtenberg, and Zilberman, 1992; Saha, Shumway, and Havenner, 1997; Chambers and Lichtenberg, 1994; and Carpentier and Weaver, 1997), an exponential specification is used:

$$G(Z_j, \alpha_k) = 1 - e^{-\alpha_{0k} - \alpha_{1k}Z_j}, \tag{4}$$

where α_k is a vector of damage abatement parameters that differ between participants $(k = p)$ and nonparticipants $(k = n)$ in the MCE scouting program.

We use a noncentral exponential specification ($\alpha_{0k} \neq 0$) because, as pointed out by Chambers and Lichtenberg (1994), setting $\alpha_{0k} = 0$ corresponds to assuming that pesticides are essential inputs. The noncentral specification allows this hypothesis to be tested formally and simply.

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[1] It is possible that pesticide use affects the productivity of normal inputs. Oude Lansink and Carpentier (2001) develop a specification that permits interactions between damage abatement (rather than pesticides) and normal inputs, and apply it to data from Dutch farms whose output is a mixture of potatoes, sugar beets, wheat, and other crops. Although they were unable to conduct formal statistical tests, their results appear consistent with the hypothesis of weak separability maintained here.

In this model, pesticide demand of farmers using extension-trained and certified scouts may differ in two ways from that of farmers scouting themselves or using chemical dealer employees. First, the parameters of the damage abatement function α_k may differ because extension-trained scouts may provide different treatment recommendations than scouts employed by chemical dealers or farmers doing their own scouting. This hypothesis is stated as $\alpha_p \neq \alpha_n$. Second, the unobserved variables comprising the white noise error may differ in distribution. Letting σ_k denote the variance of u_j, this hypothesis is expressed as $\sigma_p \neq \sigma_n$. Letting P denote the set of participants and N the set of nonparticipants, the most general form of the likelihood function of the model specified by equations (3) and (4) is thus:

$$\text{(5)} \qquad \ln \mathrm{L} = \Omega + T_p \ln(\sigma_p) + \sum_{j \in P} \left(\frac{\ln\left(\dfrac{v}{R_j}\right) - \ln\left(\dfrac{G'(Z_j, \alpha_p)}{G(Z_j, \alpha_p)}\right)}{\sigma_p} \right)^2 + T_n \ln(\sigma_n) + \sum_{j \in N} \left(\frac{\ln\left(\dfrac{v}{R_j}\right) - \ln\left(\dfrac{G'(Z_j, \alpha_n)}{G(Z_j, \alpha_n)}\right)}{\sigma_n} \right)^2,$$

where Ω is a constant, T_p is the number of participants, and T_n is the number of nonparticipants.

Three possible circumstances are examined under which participants and nonparticipants might differ. The first is where participants and nonparticipants differ in terms of both the damage-control function parameters and the variance of the error ($\alpha_p \neq \alpha_n$ and $\sigma_p \neq \sigma_n$). The remaining two scenarios are where participants and nonparticipants differ in terms of either the damage-control function parameters ($\alpha_p \neq \alpha_n$) or the variance of the error ($\sigma_p \neq \sigma_n$), but not necessarily both.

Data

IPM programs are typically developed by public-sector research, either at the federal level or through the land grant university system. Dissemination of these programs is usually the responsibility of agricultural extension in each state (Wearing, 1988). A typical IPM implementation process consists of demonstrations on a few farms followed by provision of advice at subsidized rates (including free-of-charge), with subsidies phased out over the implementation period. In the case of scouting, state agricultural experiment station and extension personnel typically develop scouting protocols and train scouts. The services of extension-trained and -certified scouts are offered to farmers first at no charge, then at charges that increase until they reach full cost, at which point the implementation process is considered finished. These IPM protocols are also disseminated via fact sheets or other publications, and thus may be accessible to those not specifically trained by extension—e.g., individual farmers or chemical dealer employees.

This study uses data from a survey conducted at the end of one such implementation program. In 1972, Maryland Cooperative Extension (MCE) initiated a pilot program to test scouting protocols on the state's four major field crops: corn, soybeans, alfalfa, and small grains. MCE then provided scouting free of charge until 1979. Beginning in 1980, farmers were required to pay for scouting services, but at subsidized rates. Beginning in 1985, growers were required to pay the full cost of scouting, but MCE continued to train and supervise scouts. In 1992, supervision of scouts was phased out as well, although MCE continues to provide training and certification of scouts.

Personal interviews of 123 field crop growers in two Maryland counties were conducted in 1991 by MCE staff and MCE-trained IPM consultants. The main purpose of the survey was to determine the effect of MCE scouting recommendations on pesticide use. A secondary purpose was to investigate whether farmers using MCE scouting differed from those who did not in terms of demographic characteristics and attitudes toward pesticides. The sample included all growers who used MCE scouting in two counties with the strongest programs. One was in central Maryland while the other was on the Eastern Shore. A matching sample of farmers who did not use MCE scouting was selected from the Maryland Department of Agriculture's master list of all farmers in each of those two counties plus two adjacent counties without a strong MCE IPM program. Thus, the sample resembled that of a case control study of the kind widely used in medicine and epidemiology.

Most of the respondents (93) came from central Maryland. Thirty-eight percent (47 farmers) used MCE scouting in 1991.[2] Thirty-five of the farmers using MCE scouting grew corn, 30 grew soybeans, 20 grew alfalfa, and 16 grew small grains. Sixty-five of the 76 farmers not using MCE scouting grew corn, 57 grew soybeans, 25 grew alfalfa, and 34 grew small grains.

The survey inquired about farming operations, human capital and demographic information, disease, weed, and pest problems encountered, attitudes toward pest management, practices used in pest management, pesticide use, and sources of information consulted in making pest management decisions. Information collected about farming operations included the size of the operation (acres farmed), annual sales of farm products, time devoted to farming, and percentage of income obtained from farming. All were reported as categorical variables. Other data obtained were yield and acreage of each of the four field crops in 1991, the percentages of sales from field crops, livestock, and other crops in 1991, and average yields of each of the four field crops during 1985–1990.

Human capital and demographic information included age, level of education, and farming experience (all reported as categorical variables), and whether the respondent was a certified pesticide applicator.[3] Farmers were asked to report the two most important insect and disease problems and the three most important weed problems in each crop. Information on attitudes toward pest management included the factors each farmer found important in making pest management decisions, whether the respondent knew anyone who had become ill as a result of pesticide exposure, and whether the respondent would be willing to pay a higher price for a pesticide that posed less risk to human health or groundwater. Farmers were asked which nonchemical pest control

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[2] Eight farmers who did not use MCE scouting in 1991 had used it in prior years. These individuals were classified as nonparticipants. None of the farmers in the sample received MCE training as scouts themselves.

[3] Certified applicator training is legally required to apply pesticides classified by the Environmental Protection Agency as "restricted use." The certification curriculum is oriented toward pesticide application methods. It covers laws and regulations governing the use of restricted use pesticides as well as general information on pest control, health and environmental safety, and pest management application technology. The curriculum does not cover IPM methods, including scouting.

techniques they used as well as which pesticides. For each pesticide used, application rates and acreage treated were recorded for each crop. Finally, respondents were asked from which sources they received the majority of their information regarding pest management and pesticide use.

As noted above, the sample was constructed in a manner consistent with a case control study with the expectation that the only difference between the two groups of farmers would be the use of MCE scouting. That expectation was largely borne out for the sample as a whole in terms of farm operating characteristics, human capital, demographics, pest problems encountered, factors considered important in making pest management decisions, and attitudes about pesticides.

Participants and nonparticipants in the MCE scouting program were compared using t-tests for continuous variables and χ^2 tests for categorical variables applied to the entire set of respondents. The only statistically significant difference between the two groups with regard to farm operating characteristics, human capital, and demographics occurred in education. As can be seen from table 1, a higher percentage of those using MCE scouting had a college degree or postgraduate education. Respondents were asked to list the two most important insect pests and three most important weeds for each crop they raised. There were no statistically significant differences (and very little quantitative difference) in the percentages of participants and nonparticipants reporting each insect pest and weed species (table 2). Respondents were also asked to identify the three most important factors in making decisions about whether to apply pesticides and the two most important factors in pesticide selection. The only statistically significant (and substantive) difference lay in the source of advice. Participants were more likely to rely on advice from scouts or extension personnel, whereas nonparticipants were more likely to rely on dealers or applicators (table 3).

Estimation of the parameters of the model in equation (5) requires observations on three variables: pesticide use (Z_j), the price of pesticides (v), and expected revenue (R_j). We assumed nonjointness in production (so that pesticide demand was estimated separately for each crop category) and constant returns to scale (so that output could be expressed in per acre terms). Pesticide use was also measured on a per acre basis, i.e., $z_j = Z_j/A_j$. Thus, the likelihood function becomes:

$$\ln \mathrm{L} = K + T_p \ln(\sigma_p) + \sum_{j \in P} \left(\frac{\ln\left(\frac{v}{r_j}\right) - \ln\left(\frac{G'(z_j, \alpha_p)}{G(z_j, \alpha_p)}\right)}{\sigma_p} \right)^2 + T_n \ln(\sigma_n) + \sum_{j \in N} \left(\frac{\ln\left(\frac{v}{r_j}\right) - \ln\left(\frac{G'(z_j, \alpha_n)}{G(z_j, \alpha_n)}\right)}{\sigma_n} \right)^2, \tag{6}$$

where $r_j = R_j/A_j$ is expected revenue per crop acre.

Many studies use the weight of pesticide active ingredient applied per acre of cropland to measure the intensity of pesticide use. A drawback of this approach is that it does not take into account differences in pesticide effectiveness. For example, pesticides with greater toxicity are applied at lower rates per acre than compounds with lower toxicity. In such cases, the lesser weight of active ingredient used does not mean less pesticide was applied. As an alternative, we measured pesticide application rates

Table 1. Farm Operation, Human Capital, and Demographic Characteristics of All Survey Respondents (N = 123 growers)

Description	Participants in MCE Scouting Program	Nonparticipants in MCE Scouting Program
Acres Operated:		
Number of respondents	47	76
< 100 acres	2%	3%
100–249 acres	32%	26%
250–499 acres	23%	42%
500–999 acres	26%	18%
1,000 acres or more	17%	11%
Annual Gross Sales of Farm Products:		
Number of respondents	47	76
< \$25,000	11%	10%
\$25,000–\$49,999	11%	13%
\$50,000–\$99,999	9%	20%
\$100,000–\$249,999	27%	39%
\$250,000–\$499,999	34%	14%
\$500,000 or more	7%	4%
Full-Time Farmer, % (N)	81% (44)	84% (71)
Percent of Time Devoted to Farming, % (N)	79% (46)	84% (75)
Percent of Income Obtained from Farming, % (N)	86% (47)	84% (74)
Distribution of Gross Farm Sales by Product:		
Number of respondents	37	71
Field crops	47%	59%
Fruit, vegetable, and specialty crops	6%	1%
Livestock and poultry	47%	40%
Respondent's Age:		
Number of respondents	46	76
< 30 years	7%	7%
30–39 years	22%	20%
40–49 years	28%	24%
50–59 years	28%	25%
60 years or more	15%	25%
Highest Level of Schooling***:		
Number of respondents	47	75
Some high school	4%	11%
High school or equivalent	36%	64%
Some college or formal training	21%	20%
Bachelors degree	26%	3%
Postgraduate education	13%	3%
Farmer is a certified pesticide applicator, % (N)	81% (47)	67% (76)

Note: Triple asterisks (***) denote statistically different at the 1% significance level.

Table 2. Most Important Insect and Weed Problems Encountered

Description		Participants in MCE Scouting Program ($N = 47$)	Nonparticipants in MCE Scouting Program ($N = 76$)
Two Most Important Insect Pests During Past 5 Years:			
CORN:	Rootworm	25%	22%
	Cutworm	16%	25%
	European corn borer	39%	39%
	Wireworm	5%	1%
	White grub	1%	2%
	Slugs	14%	12%
SOYBEANS:	Mexican bean beetle	7%	17%
	Green cloverworm	4%	8%
	Spider mites	50%	42%
	Podworms	16%	11%
	Thrips	4%	4%
	Leafhoppers	20%	19%
SMALL GRAINS:	Aphids	21%	22%
	True armyworm	26%	25%
	Grass sawfly caterpillar	10%	26%
	Cereal leaf beetle	44%	28%
ALFALFA:	Alfalfa weevil	39%	38%
	Potato leafhopper	52%	42%
	Aphids	5%	11%
	Spittlebug	4%	10%
Three Most Important Weed Problems:			
CORN:	Perennial broadleaf	11%	13%
	Perennial grass	20%	14%
	Annual broadleaf	48%	48%
	Annual grass	20%	23%
	Other	1%	2%
SOYBEANS:	Perennial broadleaf	12%	13%
	Perennial grass	18%	15%
	Annual broadleaf	2%	11%
	Annual grass	24%	16%
	Other	2%	1%
ALFALFA:	Perennial broadleaf	11%	8%
	Perennial grass	6%	6%
	Annual broadleaf	49%	62%
	Annual grass	16%	5%
	Other	17%	20%
SMALL GRAINS:	Perennial broadleaf	26%	20%
	Perennial grass	3%	1%
	Annual broadleaf	49%	43%
	Annual grass	6%	6%
	Other	17%	30%

Table 3. Most Important Factors in Selecting Pesticides and Whether to Apply Pesticides

Description	Participants in MCE Scouting Program	Nonparticipants in MCE Scouting Program
Three Most Important Factors in Deciding Whether to Apply Pesticides:	**(*N* = 47)**	**(*N* = 75)**
Always treat pests whenever detected	2%	12%
Crop history of field	23%	28%
Advice from county agent or specialist	68%***	35%***
Follow set spray routine	11%	13%
Advice from pesticide dealer or applicator	28%***	57%***
News that neighbors are having problems	2%	15%**
Evidence gathered by quick observation	11%	15%
Evidence gathered with sampling techniques and economic thresholds	45%	61%
Advice from pest management scout or consultant	89%***	33%***
Two Most Important Factors in Pesticide Selection:	**(*N* = 47)**	**(*N* = 76)**
Applicator safety	62%	61%
Safety to beneficial organisms and wildlife	51%	39%
Lower risk of groundwater contamination	47%	43%
Ease of container disposal or reuse	9%	7%
Formulation, compatibility, mixing	28%	26%
General versus restricted use pesticide	19%	25%

Note: Double and triple asterisks (**, ***) denote statistically different at the 5% and 1% significance levels, respectively.

per acre in terms of dose equivalents. The survey data contain observations on the area of each crop treated with each pesticidal chemical, the application rate used, and the application rate recommended by Maryland Cooperative Extension. The amount of formulated product applied per acre was divided by the per acre recommended application rate. The number of these dose equivalents applied per acre was calculated by multiplying the dose equivalent of each pesticide applied by the acreage treated with it, summing up over all pesticides applied, and, finally, dividing by the acreage of the crop to obtain a treated-acreage-weighted average number of dose equivalents per crop acre.

We also estimated models using the weight of pesticide active ingredients applied, as have many other studies. The aggregate weight of pesticide active ingredients applied per acre was calculated by multiplying the weight of active ingredient of each pesticide applied by the acreage treated with it, summing up over all pesticides, and then dividing by crop acreage to obtain a treated-acreage-weighted average weight of active ingredients applied per crop acre.

Prices of pesticides were obtained from dealer price lists and used to estimate pesticide expenditures. The price of the pesticides used by each farmer (v_j) was calculated by dividing total expenditures on pesticides on each crop by the total number of dose equivalents (or weight of active ingredients) applied—i.e., the price of each chemical used was weighted by its share in the total number of dose equivalents (or weight of active ingredients) applied. The survey data also contained observations on the yield of each crop during the five years preceding 1991. This variable should capture long-term variations among farmers due to such factors as human capital, land quality, and persistent pest problems. Average prices received for each crop were obtained for each county from *Maryland Agricultural Statistics* annual reports (Maryland Department of Agriculture). Naïve expectations were assumed. Specifically, expected revenue per acre (r_j) was assumed to be the product of the 1990 county average price and the average yield per acre obtained during the preceding five years. While this treatment of expectations may be overly simplistic, it should be noted that changing the treatment of expectations would simply recalibrate the parameter estimates without changing anything essential.

Summary statistics of the variables used in the econometric analysis are given in table 4. Missing information about yields and pesticide use reduced the size of the sample used in the econometric analysis.

Estimation Method

Maximum-likelihood estimators of the parameters of damage abatement (α_k) and the variance of the random error (σ_k) for each crop category were obtained using nonlinear optimization procedures (PROC NLIN and PROC MODEL) in SAS. Three models were run for each crop. The first (model I) was an unrestricted model allowing participants and nonparticipants to differ in terms of both the abatement parameters ($\alpha_p \neq \alpha_n$) and the variance of the random error ($\sigma_p \neq \sigma_n$), obtained by running separate regressions for each group. The second (model II) was a partially restricted model allowing participants and nonparticipants to differ in terms of abatement parameters ($\alpha_p \neq \alpha_n$) but not variances of the random errors ($\sigma_p \neq \sigma_n$), obtained by running a single regression for the two groups pooled together, with a dummy variable equaling one for participants included both by itself and interacted with the quantity of pesticides applied. The third (model III) was a fully restricted model assuming that participants and nonparticipants had the same abatement parameters ($\alpha_p \neq \alpha_n$) and variances of the random errors ($\sigma_p \neq \sigma_n$), obtained by running a single regression for the two groups pooled together.

Likelihood-ratio tests of our three hypotheses were constructed from these models using the following sequential procedure. First, we tested whether the abatement parameters and the variances of the random errors were simultaneously equal for participants and nonparticipants by comparing models I and III. Second, we tested whether the variances of the random errors only were equal for participants and nonparticipants by comparing models I and II. The hypothesis of equal variances could not be rejected for any crop, indicating that any significant differences between models I and III were due to differences in the abatement parameters alone. This result was double-checked by testing whether the abatement parameters were equal for participants and nonparticipants under a maintained assumption of equal variances of the random errors using a comparison of models II and III.

All of the models were estimated (and hypothesis tests conducted) using both dose equivalents per acre and the weight of active ingredients per acre as measures of pesticide use. The two procedures for measuring pesticide use gave largely the same results for corn and soybeans in terms of the statistical significance and magnitudes of the abatement function coefficients. The same is true of the intercept terms of the abatement function in the models for alfalfa and small grains. However, the slope coefficients for both alfalfa and small grains were much smaller than those obtained when

Table 4. Means of Variables Used in the Econometric Analysis

Variable	Participants in MCE Scouting Program	Nonparticipants in MCE Scouting Program
Alfalfa:	**(*N* = 18 observations)**	**(*N* = 17 observations)**
Crop acres	53.68	43.56
Revenue per acre ($)	659.04	632.55
Expenditures on pesticides per acre ($)	8.91	7.09
No. of dose equivalents applied per acre	2.13	4.09
Pesticide active ingredients applied per acre (lbs.)	0.87	0.98
Corn:	**(*N* = 28 observations)**	**(*N* = 45 observations)**
Crop acres	233.03	288.29
Revenue per acre ($)	286.05	276.47
Expenditures on pesticides per acre ($)	29.22	26.26
No. of dose equivalents applied per acre	12.53	11.43
Pesticide active ingredients applied per acre (lbs.)	5.20	4.82
Small Grains:	**(*N* = 16 observations)**	**(*N* = 29 observations)**
Crop acres	131.25	178.35
Revenue per acre ($)	147.47	141.52
Expenditures on pesticides per acre ($)	5.69	4.92
No. of dose equivalents applied per acre	3.09	2.93
Pesticide active ingredients applied per acre (lbs.)	0.10	0.11
Soybeans:	**(*N* = 25 observations)**	**(*N* = 45 observations)**
Crop acres	232.28	282.20
Revenue per acre ($)	243.53	230.19
Expenditures on pesticides per acre ($)	40.02	34.26
No. of dose equivalents applied per acre	4.22	5.99
Pesticide active ingredients applied per acre (lbs.)	2.20	2.56

pesticide use was measured in terms of weight of active ingredients per acre, and neither was significantly different from zero at a 5% significance level or better. The lack of statistical significance may have been due to the small number of observations available (35 for alfalfa, 45 for small grains) and/or the lack of variation in pesticide use when measured this way (the coefficient of variation of pesticide use measured in terms of dose equivalents was only 0.33, compared to 1.22 when pesticide use was measured in terms of weight of active ingredients).

The corn models presented some special problems. Regardless of which measure of pesticide use was included, the models converged but none of the estimated parameters were significantly different from zero and the slope coefficient in the pooled model could not be estimated. However, *F*-tests indicated that the intercept and slope coefficients, taken together, were significantly different from zero at a significance level well below 1%. Subsequent inspection of the likelihood functions for the unrestricted model revealed the existence of global minima in the slope parameter α_{1k} for both participants and nonparticipants. The likelihood functions were essentially flat in the constant parameter α_{0k} dimension for both participants and nonparticipants, however. Since this pattern is not inconsistent with the hypothesis that the constant term $\alpha_{0k} = 0$ in both cases, we estimated all three models for corn without constant terms for both measures of pesticide use.

Estimation Results

Differences Between Participants and Nonparticipants

As the test statistics reported in table 5 indicate, the likelihood-ratio tests show a significant difference in the abatement parameters of participant and nonparticipant soybean growers, although the hypothesis that participants and nonparticipants have the same variances of the random errors cannot be rejected. In contrast, the null hypothesis that the abatement parameters and the variances of the random errors are the same for participants and nonparticipants could not be rejected for alfalfa, corn, and small grains. Thus, there appears to be no significant difference between participants and nonparticipants with respect to either abatement function parameters or variances of the random errors in alfalfa, corn, and small grain production. In other words, MCE scouting reduced pesticide demand on soybeans, but not on alfalfa, corn, and small grains.

Estimated Pesticide Productivity

Since the likelihood-ratio tests indicated no significant difference in either abatement parameters or variances of the random errors for alfalfa, corn, and small grains, the parameters obtained by pooling participant and nonparticipant data were used to examine pesticide productivity in these crops (table 6). The likelihood-ratio test revealed a significant difference in the abatement parameters of participants and nonparticipants for soybeans; however, the coefficient of the participant dummy was not significantly different from zero at a 5% significance level, indicating no difference in the constant term of the abatement function (table 6). A model allowing a shift in the slope of the abatement function (the coefficient of pesticides) but not in the constant term was therefore used to examine pesticide productivity for soybeans.

The constant term of the abatement function (α_0) was significantly different from zero for soybeans, suggesting pesticides are not an essential input for this crop—damage is less than 100% when no pesticides are used. Even so, soybeans appear quite vulnerable to pest pressure, such that production may not be economically viable without pesticides even if it is physically possible. Estimated crop loss with zero pesticide use ($e^{-\alpha_0}$) is 47% when pesticide use is measured in terms of dose equivalents and 59% when pesticide use is measured in terms of weight of active ingredients.

As noted above, the likelihood function for corn was flat in the α_0 dimension, a result consistent with pesticides being essential for production.

The constant term of the abatement function for alfalfa was significantly different from zero and quite large in magnitude, suggesting a low level of crop loss in the absence of pesticide use: 9% when pesticide use is measured based on dose equivalents and 5% when pesticide use is measured based on weight of active ingredients. These figures imply that pesticides contribute very little to alfalfa production.

The constant term of the abatement function for small grains was significantly different from zero when pesticides were measured in the context of weight of active ingredients, and were similar in magnitude in both models. Estimated crop loss in the absence of pesticides was 23% when pesticides were measured in terms of dose equivalents and 17% when pesticides were measured in terms of the weight of active ingredients.

Table 5. Likelihood-Ratio Test Statistics for Differences in Pesticide Demand Between Participants and Nonparticipants

		Hypothesis Tested:		
Crop	Number of Observations	Abatement Parameters and Variances Different	Only Variances Different	Only Abatement Parameters Different (assuming equal variances)
Pesticides Measured in Dose Equivalents per Acre:				
Alfalfa	35	0.7428	N/A	N/A
Corn	73	0.2698	0.0000	0.2698
Small Grains	45	1.3483	N/A	N/A
Soybeans	70	10.5459**	0.0017	10.5459***
Pesticides Measured in Pounds of Active Ingredients per Acre:				
Alfalfa	35	1.1279	0.0000	1.1279
Corn	73	0.1467	0.0000	0.1467
Small Grains	45	3.3551	0.0000	3.3551
Soybeans	70	28.1309***	0.0000	28.1309***
χ^2 5% critical value		7.8147	3.8415	5.9915
[degrees of freedom]		[3]	[1]	[2]

Notes: Double and triple asterisks (**, ***) denote statistically different from zero at the 5% and 1% significance levels, respectively. N/A indicates the model with IPM dummies did not converge; hence tests were not conducted.

The coefficient of pesticides (α_1) was significantly different from zero for both corn and soybeans. The pesticide coefficients for participating soybean growers were much larger than those of nonparticipants (twice as much when pesticide use is measured with respect to dose equivalents, and over 10 times as much when pesticide use is measured with respect to weight of active ingredients), indicating nonparticipants' pesticide demand is substantially higher than that of participants. Consequently, as expected, soybean growers using MCE scouting had lower pesticide demand curves than those using scouting by chemical dealer employees or assessing infestation levels themselves, i.e., MCE scouting does appear to result in lower pesticide demand.

The coefficient of pesticides was significantly different from zero for alfalfa and small grains only when pesticides were measured in terms of the weight of active ingredients. The estimates suggest that the marginal productivity of pesticides on these crops is low. Estimated alfalfa crop loss in the absence of pesticides is quite small and becomes negligible at very low pesticide application rates. The pesticide coefficient for small grains is quite large, indicating marginal pesticide productivity declines extremely rapidly, so that the profit-maximizing application rate is quite low.

Discussion

Proponents of the view that it matters who scouts assert in essence that recommendations made by extension-trained independent crop consultants are qualitatively superior to those of chemical dealer employees or farmers themselves. The empirical results obtained here lend some support to this proposition for soybeans, but not for corn, alfalfa, or small grains. Two factors likely account for the lack of difference in pesticide demand for the latter three crops: (a) differences in the ease of scouting (and deriving recommendations), and (b) specific conditions in the year the survey was conducted.

Table 6. Abatement Function Parameter Estimates

	CROP				
				Soybeans	
Parameter	Alfalfa (N = 35 obs.)	Corn (N = 73 obs.)	Small Grains (N = 45 obs.)	Full Model (N = 70 obs.)	Final Model (N = 70 obs.)
Pesticides Measured in Dose Equivalents per Acre:					
Constant (α_0)	2.4327***		1.4582	0.6345***	0.7466***
	(0.7624)		(1.1109)	(0.1146)	(0.0774)
Slope (α_1)	0.0679	0.2374***	0.0787	0.0417***	0.0526***
	(0.0684)	(0.0181)	(0.1323)	(0.0122)	(0.0102)
Participant constant shift				0.2478	
				(0.1485)	
Participant slope shift				0.1183***	0.0626***
				(0.0449)	(0.0311)
Log likelihood	-32.2496	-45.8912	-60.7463	-55.4734	-56.9859
Pesticides Measured in Pounds of Active Ingredients per Acre:					
Constant (α_0)	2.9941***		1.7593***	0.8445***	0.5300***
	(0.2076)		(0.0604)	(0.1883)	(0.1012)
Slope (α_1)	0.6043***	0.5663***	10.2894***	0.1446***	0.0621***
	(0.1879)	(0.0445)	(0.5130)	(0.0720)	(0.0201)
Participant constant shift				-0.3550	
				(0.2140)	
Participant slope shift				0.5449***	0.6147***
				(0.1118)	(0.0942)
Log likelihood	-37.9054	-135.0337	-26.9824	-71.1533	-71.9090

Notes: Triple asterisks (***) denote statistically different from zero at the 1% significance level. Values in parentheses are asymptotic standard errors.

Skill and training are more likely to make a difference in situations where sampling and recommendations are more complex, either because of the intrinsic features of the agroecosystem or because of unusual (hence non-recurring) growing conditions in a specific year. The ease of scouting and deriving recommendations for insects differs substantially for the four crops studied here. Alfalfa and small grains are the simplest. Scouting need only be performed once a season during a short time window, sampling is easy to do, and recommendations for treatment depend only on the abundance of one specific pest on each crop. Corn is somewhat more complex. Scouting is performed during a short time window (and thus needs to be performed only once during the season), but recommendations are usually based on relative abundances of insect pests, beneficials, and other organisms as well as growing conditions generally. Soybeans are the most complex, since insect attacks can occur over a longer time frame (necessitating repeated sampling over the growing season) and treatment recommendations depend on the stage of plant growth as well as the relative abundance of insect pests, beneficials, and other organisms and general growing conditions (Dively, 2005).

The 1991 growing season in Maryland was hotter and drier than normal (Maryland Department of Agriculture, 1992). Outbreaks of podworm and spider mite are common in Maryland under these conditions; major outbreaks of both pests occurred during August and September 1991. Insect pressure on corn, in contrast, was quite low. Corn borer counts in traps that year were close to half the average. Insect pressure on alfalfa and small grains was about normal in 1991 (Dively, 2005).

A lack of difference in pesticide demand due to specific growing conditions should only be temporary, while a lack of difference due to ease of scouting and deriving recommendations should be permanent. Thus, the differences in soybean pesticide demand observed here are likely to persist, as will the lack of difference in pesticide demand on alfalfa and small grains. Firm conclusions cannot be drawn for corn since insect pressure was lower than normal in 1991.

Concluding Remarks

The widespread use of scouting and economic thresholds in U.S. agriculture would seem to be one of the major successes of public efforts to promote IPM. But some have argued that this success is more apparent than real. Proponents of this latter view note that most scouting is not performed by trained IPM consultants using scientific monitoring schemes and making recommendations according to economic thresholds derived on the basis of the best crop science available. They contend that chemical dealers may inflate scouting reports and/or use excessively low economic thresholds in order to increase pesticide sales or avoid liability for pest damage, while farmers may use excessively low treatment thresholds due to risk aversion and/or overestimation of pest pressure.

This debate has broader implications for the future of agriculture. Many new agricultural technologies (e.g., precision farming methods) are, like IPM, information-intensive (National Research Council, 1997). As in the case of scouting, chemical and equipment dealers have been and will likely continue to be among the most common providers of consulting services for use with these technologies, whereas some farmers may rely on themselves to collect and evaluate the information used in these technologies. If advanced, scientifically grounded training like that provided by independent, extension-trained consultants is needed to implement these information-intensive technologies appropriately, the potential gains from their use (in particular, environmental gains from more closely matching input application rates with crop requirements) may not be attained.

This study has used data from a survey of Maryland field crop growers to investigate this claim. Most of the growers surveyed reported using scouting. Some used scouts trained and supervised by extension; others used chemical dealer employees or scouted themselves. Our results lend partial support to those who believe that reliable scouting and treatment recommendations are provided only by consultants who are certified and trained by extension. In other words, it can matter who scouts—but it doesn't always. Soybean growers using extension-trained scouts had significantly lower pesticide demand than those who did not. However, we found no significant differences in the pesticide demands for corn, alfalfa, or small grains. Differences in the complexity of pest management likely account for the results for soybeans, alfalfa, and small grains. Pest management is considerably more complex for soybeans than for the other three crops. Scouting for insects, for example, must be conducted several times during the growing season for soybeans (compared to only once for the other three crops), and treatment recommendations depend on numerous factors, including stage of crop growth in addition to counts of insect pests and beneficials (compared to insect counts alone for alfalfa and small grains). Corn is scouted only once in Maryland, but treatment recommendations are based on a variety of factors. During the year studied, insect pressure was abnormally low; it remains possible that extension scouting would result in significantly different pesticide demand under other conditions.

The inferences to be drawn from our results are limited by the fact that our data come from a single year and a single producing region and by small sample sizes. Further investigation using larger samples and panel data is needed to resolve this issue fully. Given the mixed results obtained here, further investigation along these lines likely would be worthwhile.

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