

Does It Matter Who Scouts?

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Abstract

Scouting is the most widely used integrated pest management (IPM) technique. It has been argued that only independent crop consultants provide unbiased scouting information. In contrast, chemical dealers inflate scouting reports and/or reduce economic thresholds in order to increase pesticide sales while farmers may use excessively low treatment thresholds due to risk aversion and/or overestimation of pest pressure.. Since the majority of scouting is done by farmers and chemical dealer employees, it follows that scouting may not be a very effective means of reducing reliance on chemical pesticides. 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. Our results give partial support to those skeptical of the quality of scouting by farmers themselves and by consultants working for chemical dealers. We found that soybean growers using extension trained scouts had significantly lower pesticide demand than those using chemical dealer employees or scouting themselves. However, we found no significant differences in the pesticide demands for alfalfa, corn, and small grains. Since soybeans in Maryland are substantially more pesticide-intensive than corn, alfalfa, or small grains, these results suggest that it does matter who scouts when there is scope for substantial savings in pesticides.

JEL Categories: Q16, Q12, Q20

Key Words: integrated pest management, scouting, pesticides, pesticide demand.

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Does It Matter Who Scouts?

Integrated pest management (IPM) is an approach that combines the use of chemical pesticides with non-chemical methods to limit the damage caused by such pests as insects, weeds, diseases, and rodents. Among the non-chemical 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 non-chemical method is scouting, that is, 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 et al. 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, they were used on 78 percent of U.S. corn acreage, 77 percent of U.S. soybean acreage, 80 percent of U.S. wheat acreage, 86 percent of U.S. potato acreage, 88 percent of U.S. cotton acreage, 76 percent of U.S. fruit and nut acreage, and 71 percent of U.S. vegetable acreage (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 economic thresholds that are too low, 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 reliance on chemical pesticides.

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 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 will affect pesticide demand the same ways regardless of who scouts.

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 non-participants (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 that featured scouting reduced expenditures on pesticides significantly among California cotton growers during the early 1970s. Pingali and Carlson (1985) found that 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 that scouting may influence the frequency with which apple growers apply insecticides. None of these studies, however, compared scouting by independent crop consultants to scouting by farmers or chemical dealer employees. Fernandez-Cornejo (1996) found that tomato growers using insect scouting plus one or more other non-chemical 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 those using scouting by extension-supervised independent crop consultants with those scouting

themselves or using chemical dealer employees. We formulate maximum likelihood estimators 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 before. 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, we use the estimated parameters to discuss 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, making it appear that pesticides are underused in cases where they are actually overused. As Chambers and Lichtenberg (1994) pointed out subsequently, 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 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 (Chambers and Lichtenberg 1994). Other studies of aggregate U.S. agricultural output (Carrasco-Tauber and Moffitt 1992) and aggregate French cereal and oilseed production (Carpentier and Weaver 1997) found that damage control models fit no better (but also no worse) than generic specifications.

Like these other studies, we specify output Q as a weakly separable combination of potential yield $F(X)$ and damage abatement $G(Z, \alpha)$, where 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. If pesticides are essential, 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 essential. To this end, we employ the implicit demand specification suggested by Chambers and Lichtenberg (1995). Output of farmer j is

$$Q_j = F(X_j)G(Z_j, \mathbf{a})u_j \quad (1)$$

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

$$p(X_j, Z_j, \mathbf{a}) = pF(X_j)G(Z_j, \mathbf{a})u_j - w \cdot X_j - vZ_j, \quad (2)$$

where p is the crop price, w is a vector of the unit prices of normal inputs, and v is the unit price

of pesticides. The first order condition for profit maximization can be written

$$\ln \frac{v}{R_j} - \ln \frac{G'(Z_j, \mathbf{a})}{G(Z_j, \mathbf{a})} = \ln u_j, \quad (3)$$

where $R_j = pF(X_j)G(Z_j, \alpha)$ 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 that it have the attributes of a cumulative distribution function. Like other empirical studies (Babcock, Lichtenberg, and Zilberman 1992, Saha, Shumway, and Havenner 1997, Chambers and Lichtenberg 1994, and Carpentier and Weaver 1997) we use an exponential specification

$$G(Z_j, \mathbf{a}_k) = 1 - e^{-\alpha_{0k} - \alpha_{1k} Z_j}, \quad (4)$$

where α_k is a vector of damage abatement parameters that differs between participants ($k = p$) and non-participants ($k = n$) in the MCE scouting program. Aside from computational convenience, the exponential is one of the few functional forms that meets all of the restrictions of the damage control hypothesis. In particular, it is defined over the positive real numbers. The other functional forms suggested by Lichtenberg and Zilberman (1986) are not: The support of the logistic distribution is $(-\infty, +\infty)$ while the lower supports of the Pareto, and Weibull distributions are positive real numbers (Johnson, Kotz, and Balakrishnan 1994).

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

In this model, pesticide demand of farmers using extension-trained and certified scouts may differ from that of farmers scouting themselves or using chemical dealer employees in two ways. 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 $\alpha_p \neq \alpha_n$. 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 $\sigma_p \neq \sigma_n$. The most general form of the likelihood function of the model specified by equations (3) and (4) is thus

$$\ln L = \Omega + T_p \ln \mathbf{s}_p + \sum_j \left(\frac{\ln \frac{v}{R_j} - \ln \frac{G'(Z_j, \mathbf{a}_p)}{G(Z_j, \mathbf{a}_p)}}{\mathbf{s}_p} \right)^2 + T_n \ln \mathbf{s}_n + \sum_j \left(\frac{\ln \frac{v}{R_j} - \ln \frac{G'(Z_j, \mathbf{a}_n)}{G(Z_j, \mathbf{a}_n)}}{\mathbf{s}_n} \right)^2 \quad (5)$$

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

We examined three possible ways participants and non-participants might differ. The first is where participants and non-participants 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 are where participants and non-participants differ in terms of either the damage control function parameters ($\alpha_p \neq \alpha_n$ and $\sigma_p = \sigma_n$) or the variance of the error ($\alpha_p = \alpha_n$ and $\sigma_p \neq \sigma_n$) but not 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 may thus 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. 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 towards 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) had used MCE scouting. 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, perceptions of disease, weed, and pest problems, attitudes toward pest management, practices used in pest management, pesticide use, and sources of information consulted in making pest management decisions. Information obtained 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. Also 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 crop categories 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. Farmers' perceptions of pest problems were measured categorically as the two most important insect and disease problems and 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 non-chemical pest control 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 the manner of 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 in terms of farm operating characteristics, human capital and demographics, and attitudes about pesticides. We compared participants and non-participants in the MCE scouting program using t-tests for continuous variables and χ^2 tests for categorical variables. Aside from the use of MCE scouting, the only statistically significant difference between the two groups occurred in education: A higher percentage of those using MCE scouting had a college degree or postgraduate education. Most of the farmers who did not participate in the MCE scouting program did not apply pesticides according to a preventive schedule; rather, they either scouted themselves (61 percent), had scouting done by chemical dealers or applicators (57 percent), or both.

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). As is standard, we also assumed that the appropriate measure of the intensity of pesticide use on each crop was the weight of pesticide active ingredient applied per acre of cropland, $z_j = Z_j/A_j$. In this case, the likelihood function becomes

$$\ln L = K + T_p \ln \mathbf{s}_p + \sum_j \left(\frac{\ln \frac{v}{r_j} - \ln \frac{G'(z_j, \mathbf{a}_p)}{G(z_j, \mathbf{a}_p)}}{\mathbf{s}_p} \right)^2 + T_n \ln \mathbf{s}_n + \sum_j \left(\frac{\ln \frac{v}{r_j} - \ln \frac{G'(z_j, \mathbf{a}_n)}{G(z_j, \mathbf{a}_n)}}{\mathbf{s}_n} \right)^2$$

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

The survey data contain observations on the area of each crop treated with each pesticidal chemical and the application rate used. As noted above, we aggregated pesticides by weight of active ingredient applied, then divided by crop acreage to obtain the measure of pesticide use per acre z_j . 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 weight of active ingredients applied, i.e., the price of each chemical used was weighted by its share in the total weight of active ingredients applied. The survey data also contained observations on the yield of each crop during the 5 years preceding 1991. This variable should capture long term variations among farmers in terms of 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. Naïve expectations were assumed: 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 5 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 these variables are given in Table 1. Missing information about yields and pesticide use reduced the size of the sample used in the econometric analysis. The sample utilized included 35 alfalfa growers, 18 of whom used MCE scouting; 73 corn growers, 28 of whom used MCE scouting; 44 small grain growers, 16 of whom used MCE scouting; and 70 soybean growers, 25 of whom used MCE scouting.

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 the nonlinear optimization procedure (PROC NLIN) in SAS. Estimators were computed using Marquardt's algorithm. Three models were run for each crop. The first was an unrestricted model allowing participants and non-participants 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 was a partially restricted model allowing participants and non-participants to differ in terms of abatement parameters ($\alpha_p \neq \alpha_n$) but not variances of the random errors ($\sigma_p = \sigma_n$), 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 was a fully restricted model assuming that participants and non-participants had the same abatement parameters ($\alpha_p = \alpha_n$) and variances of the random errors ($\sigma_p = \sigma_n$), obtained by running a single regression for the two groups pooled together. Likelihood ratio tests of our three hypotheses were constructed from these three regressions.

The corn model presented some special problems. While the models converged, 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 percent. Subsequent inspection of the likelihood functions for the unrestricted model indicated the existence of global minima in the slope parameter α_{1k} for both participants and non-participants. The likelihood functions were essentially flat in the constant parameter α_{0k} dimension for both participants and non-participants, however. Since this pattern is not inconsistent with a hypothesis that the constant term $\alpha_{0k} = 0$ in both cases, we estimated all three models without constant terms.

Estimation Results

Differences between Participants and Non-Participants

As the test statistics in Table 2 indicate, the likelihood ratio tests indicate a significant difference in the abatement parameters of participant and non-participant soybean growers, although the hypothesis that participants and non-participants 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 non-participants could not be rejected for alfalfa, corn, and small grains. Thus, there appears to be no significant difference between participants and non-participants in terms of either abatement function parameters or variances of the random errors in any of these three crop categories. In other words, MCE scouting and scouting by farmers and chemical dealers resulted in identical pesticide demand functions, i.e., scouting by chemical dealer employees or by farmers does not appear to result in greater pesticide demand than scouting by independent crop consultants.

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 non-participant data were used to examine pesticide productivity in these crops (Table 3). The likelihood ratio test indicated a significant difference in the abatement parameters of participants and non-participants for soybeans; however, the coefficient of the participant dummy was not significantly different from zero at a 5 percent significance level, indicating no difference in the constant term of the abatement function (Table

3). A model allowing a shift in the slope of the abatement function (the coefficient of pesticides) but not in the constant term was thus used to examine pesticide productivity for soybeans.

The constant term of the abatement function α_0 was significantly different from zero for three of the four crops (alfalfa, small grains, soybeans), indicating that pesticides are not essential inputs for these crops. The constant term for alfalfa was quite large, indicating that it is not highly vulnerable to pest pressure. Estimated crop loss with zero pesticide use ($e^{-\alpha_0}$) is 5 percent. Small grains appear more vulnerable to pest pressure, with estimated crop loss at zero pesticide use equal to 17 percent. Soybeans appear quite vulnerable to pest pressure, with estimated crop loss at zero pesticide use equal to 59 percent. 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 coefficient of pesticides was significantly different from zero for all four crops. The pesticide coefficient in the small grains abatement function was quite large, suggesting that the marginal product of pesticides declines very rapidly, a result consistent with the low pesticide intensity of these crops. The pesticide coefficients for corn and alfalfa were smaller, suggesting more gradually decreasing marginal productivity. The pesticide coefficient for participating soybean growers was roughly commensurate with those of corn and alfalfa. The pesticide coefficient for non-participating soybean growers was much smaller, however, suggesting that marginal pesticide productivity falls quite slowly and thus also that non-participants' pesticide demand is higher than participants'. Thus, 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 on soybeans in Maryland than does scouting by consultants working for chemical dealers or by farmers themselves.

Discussion

Taken together, these results suggest that it can matter who scouts—at least when the economic incentives are sufficiently large. As Table 1 indicates, Maryland farmers spend almost twice as much per acre on pesticides for soybeans than for corn, four times as much for soybeans as alfalfa, and eight times as much for soybeans as small grains. Higher pesticide expenditures suggest that the potential cost savings are greater for soybeans than any of the other crops considered here. Greater potential cost savings make it more likely that farmers will find it profitable to invest in more accurate but more costly monitoring on soybeans than on any of these other crops.

It possible that there are differences in participants' and non-participants' pesticide demands on these other crops—especially alfalfa and small grains—but that the econometric model used here lacks sufficient power to distinguish them. Neither alfalfa nor small grains are very pesticide-intensive. As Table 1 indicates, pesticide application rates are so low that any differences in pesticide demand between participants and non-participants are probably quite small. The number of observations on these crops (35 alfalfa growers, 45 small grain growers) is small as well. If differences between participants and non-participants' demands do exist, they may be too small to distinguish given the small sample sizes. Even if such differences do exist, however, they are probably too small to matter for policy purposes.

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 performed by chemical dealer employees or by farmers themselves. They believe that chemical dealers inflate scouting reports and/or reduce economic thresholds in order to increase pesticide sales 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. An obvious fear is that consultants employed by dealers may provide biased information in order to inflate chemical or equipment sales. In other words, if consultants employed by dealers essentially subvert IPM, they will likely do the same for precision farming technologies.

We use data from a survey of Maryland field crop growers to investigate this claim. Most of the growers surveyed used scouting. Some used scouts trained and supervised by extension while others used chemical dealer employees or scouted themselves. Our results give partial support to those skeptical of the quality of scouting by farmers themselves and by consultants working for chemical dealers. We found that soybean growers using extension trained scouts had significantly lower pesticide demand than those using chemical dealer

employees or scouting themselves. However, we found no significant differences in the pesticide demands for alfalfa, corn, and small grains. Since soybeans in Maryland are substantially more pesticide-intensive than corn, alfalfa, or small grains, these results suggest that it does matter who scouts whenever there is scope for substantial savings in pesticides. When potential savings from more accurate monitoring are smaller, though, farmers' reliance on their own monitoring or on advice from consultants employed by chemical dealers does not necessarily increase pesticide use.

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. The mixed results obtained here suggest that further investigation using larger samples and panel data might well be worthwhile.

References

Bruce A. Babcock, Erik Lichtenberg, and David Zilberman, "The Impacts of Damage Control on the Quality and Quantity of Output", American Journal of Agricultural Economics 74(1992): 163-172..

Alain Carpentier and Robert D. Weaver, "Damage Control Productivity: Why Econometrics Matters", American Journal of Agricultural Economics 79(1997): 47-61.

Catalina Carrasco-Tauber and L. Joe Moffitt, "Damage Control Econometrics: Functional Specification and Pesticide Productivity", American Journal of Agricultural Economics 74(1992): 158-162.

Robert G. Chambers and Erik Lichtenberg, "Estimating Aggregate Pest Damage in U.S. Agriculture", Working Paper No. 93-04, Department of Agricultural and Resource Economics, University of Maryland, College Park, 1995.

Robert G. Chambers and Erik Lichtenberg, "Simple Econometrics of Pesticide Productivity", American Journal of Agricultural Economics 76(1994): 407-417.

Economic Research Service, "Pest Management on Major Field Crops", AREI Updates No. 1, U.S. Department of Agriculture, February 1997.

Jorge Fernandez-Cornejo, "The Microeconomic Impact of IPM Adoption: Theory and Application", Agricultural and Resource Economics Review 25(1996): 149-160.

Bryan Hubbell, "Estimating Insecticide Application Frequencies: A Comparison of Geometric and Other Count Data Models", Journal of Agricultural and Applied Economics 29(1997): 225-242.

Bryan Hubbell and Gerald A. Carlson, "Effects of Insecticide Attributes on Within-Season Insecticide Product and Rate Choices: The Case of U.S. Apple Growers", American Journal of Agricultural Economics 80(1998): 382-396.

Marcus Kogan, "Integrated Pest Management: Historical Perspectives and Contemporary Developments", Annual Review of Entomology 43(1998): 243-270.

Maryland Department of Agriculture, Maryland Agricultural Statistics Summary for 1992. Annapolis, Maryland, 1993.

National Research Council, Precision Agriculture in the 21st Century: Geospatial and Information Technologies in Crop Management. Washington, DC: National Academy Press, 1997.

George W. Norton and Jeffrey Mullen, “Economic Evaluation of Integrated Pest Management Programs”, Virginia Cooperative Extension Publication 448-120, 1994.

Pedigo, Larry P., Scott H. Hutchins, and Leon G. Higley, “Economic Injury Levels in Theory and Practice”, Annual Review of Entomology 31, 341-368, 1986.

Atanu Saha, C. Richard Shumway, and Arthur Havenner, “The Economics and Econometrics of Damage Control” American Journal of Agricultural Economics 79(1997): 773-785.

Ann Vandeman, Jorge Fernandez-Cornejo, Sharon Jans, and Biing-Hwan Lin, “Adoption of Integrated Pest Management in U.S. Agriculture”, Agriculture Information Bulletin No. 707, Economic Research Service, U.S. Department of Agriculture, September 1994.

C.H. Wearing, “Evaluating the IPM Implementation Process”, Annual Review of Entomology 33(1988): 17-38.

David Zilberman, David Sunding, Michael Dobler, Mark Campbell, and Andrew Manale, “Who Makes Pesticide Use Decisions: Implications for Policy Makers”, in Pesticide Use and Produce Quality, Farm Foundation, Oak Brook, IL, October 1994.

Table 1. Means of Variables Used in the Econometric Analysis

	Participants in MCE Scouting Program	Non-Participants in MCE Scouting Program
Alfalfa		
Crop Acres	53.24	43.76
Revenue per Acre	659.04	632.55
Expenditures on Pesticides per Acre	10.82	9.00
Pounds of Pesticide Active Ingredients Applied per Acre	0.85	0.81
Number of Observations	18	17
Corn		
Crop Acres	268.14	288.29
Revenue per Acre	286.05	276.47
Expenditures on Pesticides per Acre	27.46	26.63
Pounds of Pesticide Active Ingredients Applied per Acre	4.99	4.87
Number of Observations	28	45
Small Grains		
Crop Acres	131.25	190.86
Revenue per Acre	147.47	141.53
Expenditures on Pesticides per Acre	5.66	5.16
Pounds of Pesticide Active Ingredients Applied per Acre	0.10	0.11
Number of Observations	16	29
Soybeans		
Crop Acres	250.05	282.53
Revenue per Acre	236.11	229.66
Expenditures on Pesticides per Acre	40.02	34.26
Pounds of Pesticide Active Ingredients Applied per Acre	2.20	2.56
Number of Observations	25	45

Table 2. Likelihood Ratio Test Statistics for Differences in Pesticide Demand between Participants and Non-Participants

Crop	Number of Observations	Hypothesis Tested:		
		Abatement Parameters and Variances Different	Abatement Parameters Only Different	Variances Only Different
Alfalfa	35	1.1279	1.1279	0
Corn— Slope and Intercept	73	0.1467	0.1467	1.6209E-14
Corn— Slope Only	73	0.0869	0.0811	0.01207
Small Grains	45	3.3551	3.3551	0
Soybeans	70	28.1309**	28.1309**	0
Chi-Squared 5% Critical Value		7.8147	5.9915	3.8415
Degrees of Freedom		3	2	1

** Significantly different from zero at a 1 percent significance level.

* Significantly different from zero at a 5 percent significance level.

Table 3. Abatement Function Parameter Estimates

Parameter	Crop				
	Alfalfa	Corn	Small Grains	Soybeans	
				Full Model	Final Model
Constant (α_0)	2.9941** (0.2076)		1.7593** (0.0604)	0.8445** (0.1883)	0.5290** (0.1012)
Slope (α_1)	0.6043** (0.1879)	0.5663** (0.0445)	10.28938** (0.5130)	0.1446** (0.0720)	0.0620** (0.0201)
Participant Constant Shift				-0.3550 (0.2140)	
Participant Slope Shift				0.5449** (0.1118)	0.6152** (0.0942)
Number of Observations	35	73	45	70	70
Log-likelihood	-44.8822	-135.0337	-26.9824	-71.1533	-71.9090

Asymptotic standard errors in parentheses.

** Significantly different from zero at a 1 percent significance level.

* Significantly different from zero at a 5 percent significance level.