ELSEVIER

Agricultural Economics 18 (1998) 145–155

AGRICULTURAL ECONOMICS

Environmental and economic consequences of technology adoption: IPM in viticulture [1]

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Accepted 11 November 1997

Abstract

The impact of integrated pest management (IPM) on pesticide use, toxicity and other environmental characteristics, yields, and farm profits is examined for grape growers. The method is generally applicable for technology adoption and accounts for self-selectivity, simultaneity, and theoretical consistency. IPM adopters apply significantly less insecticides and fungicides than nonadopters among grape producers in six states, accounting for most of the U.S. production. Both the average toxicity and the Environmental Impact Quotient decrease slightly with adoption of insect IPM, but remain about the same for adopters and nonadopters of IPM for diseases. The effect of IPM adoption on yields and variable profits is positive but only significant for the case of IPM for diseases, i.e., the adoption of IPM for diseases increases yields and profits significantly. Published by Elsevier Science B.V.

Keywords: Pesticide use; Toxicity; Integrated pest management; Grape production; Self-selection

1. Introduction

Despite their positive effect on agricultural production, evidenced by the willingness of U.S. farmers to spend US$7.7 billion on pesticides in 1995 (USDA, 1997), the potential effects of pesticides to human health and the environment have caused increased concern Huang et al., 1994. In 1993, the U.S. Department of Agriculture (USDA), the Food and Drug Administration, and the Environmental Protection Agency pledged to work together to reduce the health and environmental risks associated with pesticide use. As Integrated Pest Management (IPM) techniques were designed to address some of the health and environmental concerns of pesticides, the USDA has set a goal for the use of IPM on 75% of U.S. farmland by the year 2000.

Fruit and vegetable production is particularly intensive in pesticides. Per acre expenditures on pesticides by fruit and vegetable growers are nearly seven times the agricultural average (Fernandez-Cornejo et al., 1994). In addition, concerns about pesticide residues are especially important in fruits and vegetables, often consumed with little postharvest processing National Academy of Sciences, 1987. Grape was the top U.S. fruit crop in terms of acreage (761,000) and value of production (US$1.8 billion) in 1994 (USDA, 1995). Grape and wine production dates back more then 4000 years and extends over

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[1] "The views expressed are those of the author and do not necessarily correspond to the views or policies of the U.S. Department of Agriculture".

0169-5150/98/$17.00 Published by Elsevier Science B.V.
PII S0169-5150(97)00054-6

all continents. Besides U.S. and traditional European producers, grapes are grown extensively in some countries in Eastern Europe, parts of the former Soviet Union, Africa (Algeria and South Africa), Australia, Asia, and South America.

IPM includes an assortment of techniques designed to maintain pest infestations at economically acceptable levels rather than attempting to completely eradicate all pests Vandeman et al., 1994. While there are several conceptual definitions of IPM, according to the USDA: ''IPM is a management approach that encourages natural control of pest populations by anticipating pest problems and preventing pests from reaching economically damaging levels. All appropriate techniques are used such as enhancing natural enemies, planting pest-resistant crops, adapting cultural management, and using pesticides judiciously.'' (USDA, 1993).

While the adoption of IPM has been analyzed by several researchers (Norton and Mullen, 1994), there are few farm-level econometric studies on the effect of IPM on pesticide use, crop yields, and farm profits (Burrows, 1983; Hall and Duncan, 1984; Wetzstein et al., 1985; Smith et al., 1987; Fernandez-Cornejo, 1996). No study has been published analyzing grape production. Moreover, little farm-level empirical research has been published on the effect of IPM on the overall toxicity and other environmental characteristics of pesticides and claims that pesticides used in IPM differ from those used on a preventive or routine schedule (Allen et al., 1987) have not been empirically examined. This paper presents a framework to examine the impact of IPM on pesticide use, toxicity and other environmental characteristics of the pesticides, crop yields, and farm profits, and calculates the impact of IPM for U.S. grape growers.

2. Potential health and environmental effects of pesticide use

The reported undesirable effects of pesticides on nontarget species, including humans, include the following: acute and chronic health effects (Clark et al., 1977; EPA, 1976b; Hayes and Vaughn, 1977); domestic animal poisonings (Cadwell et al., 1977); and effects on wild birds and mammals, fish, bees, beneficial organisms, and small organisms in the soil (Bairlein, 1990; Brown, 1978; EPA, 1976a; Martin, 1978; Van Steenwyk et al., 1975; Pimentel et al., 1991.)

A pesticide poses a risk to human health and the environment if it is toxic and if humans and other species are exposed to the pesticide (Cohrssen and Covello, 1988). Human toxicity is usually inferred from experimental data on mammalian toxicity. Mammalian toxicity includes acute (short-term) and chronic (long-term, low-level exposure) toxicity. Chronic toxicity includes carcinogenicity (capability to produce cancer), mutagenicity (ability to induce genetic changes in living cells), and teratogenicity (capability to produce malformations or serious deviations from normality).

There are hundreds of pesticide active ingredients and each has a different spectrum of pest control and a different impact on human health and the environment (Fernandez-Cornejo and Jans, 1995). Thus, it is convenient to summarize the toxicity of pesticides in an overall index. Several methods have been proposed but there is no consensus about the scales and the weights assigned to the components of the index. This paper uses the overall index of human toxicity proposed by Fernandez-Cornejo and Jans (1995). This index (LTI) is the average of three components, with equal weights, each scaled from 0 to 4, the 0 corresponding to nontoxic effect. The LAI component summarizes the acute toxicity resulting from the five different measures considered by the EPA. LAI is equal to 4 if the active ingredient belongs to toxicity category I (danger) of the EPA classification; similarly LAI is equal to 3, 2, and 1 for categories II, III, and IV, respectively. The chronic element of the index (LCI) is assigned a lower score for weaker indications of carcinogenicity. Following Hammitt (1986), LCI is equal to 4 if the pesticide is a carcinogen; LCI is equal to 2 if the pesticide is not a reported carcinogen but is a neoplastigen (or oncogenic, i.e., it can produce tumors) and is equal to 0.5 if the pesticide is neither carcinogenic nor oncogenic, but is mutagenic (indicating potential carcinogenicity). Finally, the LTI component is equal to 4 if the pesticide is teratogenic.

The potential impact of pesticides on human health and the environment is approximately quantified using the Environmental Quotient Index (Kovach et al., 1992). The EIQ has three components based on the three potentially affected elements: the farm worker, the consumer, and the ecology. The EIQ measures the impact of each pesticide active ingredient by assigning an equal weight to each of its three components and has a scale of 1 to 5. The farmworker component includes acute and chronic elements and is calculated from mammal toxicity and persistence. The consumer component is based on chronic toxicity, persistence, and sistemicity. The ecological component is calculated from fish, bird, bee, and beneficial arthropod toxicity; leaching and surface loss potential, and persistence.

3. Pesticide use and IPM in grape production

Grape production in the U.S. uses a variety of pesticides. As Table 1A shows, fungicides are applied to 93% of the acreage devoted to grape production; insecticides are used in 66% of the grape acres; and herbicides are used on 64%. Among the important fungicides used, sulfur is first followed by mancozeb, copper oxychoride sulphate, captan, and myclobuthanil (USDA, 1994). Cryolite is the most extensively used insecticide, followed by propargite, and carbaryl. Commercial bioinsecticides based on the bacterium *Bacillus thuringensis* (Bt) are only used on 2% of the acres (USDA, 1994).

The use of IPM in grape production can be traced back to the late 1950s when the grape leafhopper *Erythroneura elegantula* developed resistance to synthetic organic pesticides and biological upsets of the spider mites and the grape mealybug followed (Flaherty et al., 1992). Agricultural scientists from the University of California, supported by the grape industry, lay the groundwork to a practical management system integrating chemical, cultural, and biological controls (Flaherty et al., 1992). IPM was developed further in the 1960s with the use of predaceous mites and insects and cover crops; and in the 1970s and 1980s with the use of selective pesti-

Table 1
Bearing acreage, pesticide treated area, and IPM adoption—U.S. grape producers, 1993

A. Population (estimated; USDA, 1994)

State	Bearing acreage, thousands	Area receiving[a]		
		Herbicides, %	Insecticides, %	Fungicides, %
California	651.3	62	67	94
Michigan	11.2	90	97	100
New York	32.5	81	64	99
Oregon	4.6	52	3	99
Pennsylvania	11.0	94	74	99
Washington	32.7	72	39	52
Total	743.3	64	66	93

B. Sample (calculated from the survey)

State	Number of observations	Extent of adoption, %	
		IPM for insects	IPM for diseases
California	131	32	30
Michigan	124	40	44
New York	133	16	14
Oregon	110	na	20
Pennsylvania	107	26	22
Washington	107	35	28
Total	691	29	26

[a]Acres receiving one or more applications of a specific pesticide class.

cides, parasites, viruses, and fungus to control insects and diseases.

4. The theoretical framework

4.1. Theoretical issues

An econometric model developed to estimate the impact of IPM adoption using survey data must take into account three theoretical issues. (1) Farmers' IPM adoption decisions and pesticide use may be simultaneous due mainly to unmeasured variables correlated with both IPM adoption and pesticide demand such as size of the pest population, pest resistance, farm location, and grower perceptions about pest control (Burrows, 1983). (2) Growers are not assigned randomly to the two groups (adopters and nonadopters of IPM), but they make the adoption choices themselves. Since adopters and nonadopters may be systematically different, these differences may manifest themselves in farm performance and could be confounded with differences due purely to IPM adoption. This situation, known as self-selectivity must be corrected to prevent biasing the results (Greene, 1993). (3) The demand for pesticides is a derived demand, and must be consistent with farmers' optimization behavior, such as profit maximization.

In conclusion, model specification should allow for simultaneity and self-selectivity. In addition, the demand and supply functions should be derived from a profit (or cost) function.

4.2. The adoption decision

The adoption of a new technology is a choice between two alternatives, the traditional technology and the new one and growers are assumed to make decisions by choosing the alternative that maximizes their perceived utility (Fernandez-Cornejo et al., 1994). Thus, grower i is likely to adopt IPM if the utility of adopting, U_{i1}, is higher than the utility of not adopting, U_{i0}. However, only the binary random variable I_i (taking the value of 1 if IPM is adopted and zero otherwise) is observed, as utility is not known to the analyst with certainty and is treated as a random variable (Ben-Akiva and Lerman, 1985).

In the context of IPM adoption: $U_{ij} = V_{ij} + e_{ij}$, where V_{ij} is the systematic component of U, related to the profitabilities of adopting ($j = 1$) and not adopting ($j = 0$). Assuming that the disturbances (e_{ij}) are independently and identically normally distributed, then their difference will also be normally distributed and the probit transformation can be used to model the farmer's adoption decision. Thus, the probability of adoption equation is $P(I_k = 1) = F(\gamma'_k \boldsymbol{Z}_k)$ where I_k denotes the adoption of IPM for insects ($k = 1$) and diseases ($k = 2$), F indicates the cumulative normal distribution, and the vector $\boldsymbol{Z}$ includes the factors influencing adoption.

The equations for the adoption of IPM for insects and diseases estimated using the probit model are: $I_1 = \Sigma_j \gamma_{1j} \boldsymbol{Z}_{1j} + \mu_1$ and $I_2 = \Sigma_j \gamma_{2j} Z_{2j} + \mu_2$. The components Z_j of the vector $\boldsymbol{Z}$ include the following factors of adoption: farm size, output price, farmer education and experience, off-farm labor, use of extension and consulting services, contractual arrangements for the production/marketing of the crop, and type of grape grown (i.e., wine or table grape varieties). Both probit equations have the same regressors.

Heckman's two-step procedure (Heckman, 1976) is modified to account for simultaneity in addition to self-selectivity. The first step includes the estimation of the parameters γ_k of the probit equations. The inverse Mills ratio $\lambda_k = \phi(\gamma'_k Z/\sigma_\mu)/\Phi(\gamma'_k Z/\sigma_\mu)$ is also estimated for each observation, where $\phi(\cdot)$ and $\Phi(\cdot)$ are the density and the distribution function of the standard normal, and σ_μ is the standard deviation of μ_k (Greene, 1993; Maddala, 1983). Moreover, to account for simultaneity, I_k being endogenous, the predicted probabilities (obtained from the probit equations) are used as instrumental variables for I_k in the second stage, discussed next.

4.3. Modeling the impact of IPM

The impact of IPM on pesticide use, yields, and farm profits is examined by estimating the pesticide demand functions, the supply function, and the variable profit function as a simultaneous system. To account for self selectivity, the inverse Mills ratios λ'_k (obtained from the first stage) are appended as additional regressors to the supply, demand, and profit equations.

The well-developed restricted profit function (Diewert, 1974) is used to estimate theoretically consistent supply, demand, and profit equations (Fernandez-Cornejo, 1994). Let $\boldsymbol{Y}$ denote the vector of outputs, $\boldsymbol{X}$ the vector of variable inputs, $\boldsymbol{S}$ the vector of nonnegative quasi-fixed inputs; $\boldsymbol{R}$ is the vector of other factors such as locational or weather proxies and also includes as components the predicted probabilities of IPM adoption obtained in the first stage; $\boldsymbol{P}$ is the price vector of outputs, and $\boldsymbol{W}$ is the price vector of variable inputs. The restricted profit function is defined by:

$$\pi(\boldsymbol{P},\boldsymbol{W},\boldsymbol{S},\boldsymbol{R}) = \mathrm{Max}_{XY}(\boldsymbol{P}'\boldsymbol{Y} - \boldsymbol{W}'\boldsymbol{X};\boldsymbol{X},\boldsymbol{Y} \in T)$$

The production possibilities set T is assumed to be nonempty, closed, bounded, and convex cone. Under these assumptions on the technology, the restricted profit function is well defined and satisfies the usual regularity conditions (Diewert, 1974). In particular, with some of the inputs fixed, π is homogeneous of degree one in output and variable input prices and quasi-fixed input quantities.

Considering land (L) as a fixed input and using the homogeneity conditions, the restricted profit function can be expressed as $\pi(\boldsymbol{P},\boldsymbol{W},L,\boldsymbol{R}) = L.\tilde{\pi}(\boldsymbol{P},\boldsymbol{W},\boldsymbol{R})$, where is the per acre profit function: $\tilde{\pi} = \mathrm{Max}_{YX}(\boldsymbol{P}'\tilde{\boldsymbol{Y}} - \boldsymbol{W}'\tilde{\boldsymbol{X}})$ and $\tilde{\boldsymbol{Y}} = \boldsymbol{Y}/L, \tilde{\boldsymbol{X}} = \boldsymbol{X}/L$ are the per acre output and input quantity vectors. By Hotteling-Shephard's lemma, the per acre output supply and input demand functions are then given by $\tilde{\boldsymbol{Y}} = \partial\tilde{\pi}(\boldsymbol{P},\boldsymbol{W},\boldsymbol{R})/\partial\boldsymbol{P}$ and $\tilde{\boldsymbol{X}} = \partial\tilde{\pi}(\boldsymbol{P},\boldsymbol{W},\boldsymbol{R})/\partial\boldsymbol{W}$.

The model is empirically estimated by using a normalized quadratic variable profit function (Diewert and Ostensoe, 1988). Considering the case of a single output, grapes, imposing symmetry by sharing parameters and linear homogeneity by normalization, using the labor price as the numeraire, appending the inverse Mills ratio terms as additional regressors, and adding the disturbance terms, the per acre profit function, per acre supply function, and per acre insecticide and fungicide demand functions are:

$$\begin{aligned}\tilde{\pi} = {} & a_0 + aP + \Sigma_j b_j W_j + \Sigma_k c_k \boldsymbol{R}_k \\ & + 0.5HP^2 + \Sigma_j \mathbf{G}_{1i} PW_j + \Sigma_k \mathbf{F}_{1k} P\boldsymbol{R}_k \\ & + 0.5\Sigma_j\Sigma_i B_{ij} W_i W_j + \Sigma_k\Sigma_j E_{jk} W_j \boldsymbol{R}_k \\ & + 0.5\Sigma_j C_{ik} \boldsymbol{R}_i \boldsymbol{R}_k + \theta_{31}\lambda_1 + \theta_{41}\lambda_2 \qquad (1)\end{aligned}$$

$$\begin{aligned}\tilde{Y} = {} & a + HP + \Sigma_j \mathbf{G}_j W_j + \Sigma_k \mathbf{F}_k \boldsymbol{R}_k + \theta_{y1}\lambda_1 + \theta_{y2}\lambda_2 \\ & + \epsilon_y \qquad (2)\end{aligned}$$

$$\begin{aligned}\tilde{X}_1 = {} & b_1 + \mathbf{G}_{11} P + \Sigma_j B_{1j} W_j + \Sigma_k E_{1k} \boldsymbol{R}_k + \theta_{11}\lambda_1 \\ & + \theta_{12}\lambda_2 + \epsilon_1 \qquad (3)\end{aligned}$$

$$\begin{aligned}\tilde{X}_2 = {} & b_2 + \mathbf{G}_{21} P + \Sigma_j B_{2j} W_j + \Sigma_k E_{2k} \boldsymbol{R}_k + \theta_{21}\lambda_1 \\ & + \theta_{22}\lambda_2 + \epsilon_2 \qquad (4)\end{aligned}$$

where now, $\tilde{Y}$, P, a, H, and the ϵ's are scalars; and $\mathbf{F}$ and $\mathbf{G}$ are column matrices. The vector $\boldsymbol{R}$ includes seven components: two farm attributes (farm size and off-farm labor), a dummy for the type of grape produced, the predicted probabilities of adoption of IPM for insects and diseases obtained from the probit model, and two dummies to account for pest infestation levels.

5. Data and estimation

The data were obtained from the Agricultural Chemical Use Survey and its Economic Follow-On for fruits, administered between the fall of 1993 and the spring of 1994 by the National Agricultural Statistics Service of the U.S. Department of Agriculture. The probability sample was drawn from a list frame based on all known commercial fruit growers who have at least an acre of production. A stratified sampling technique was used, where each stratum is a mutually exclusive set of the commodities.

The survey included fresh market, processing, and wine grape crops grown in California, Michigan, New York, Oregon, Pennsylvania, and Washington, covering 743,000 acres (Table 1A) and accounting for most of the U.S. acreage (USDA, 1995). The pest management section of the survey was completed by 691 grape-producing growers (Table 1B), but after excluding observations with missing values only 609 usable observations were available for econometric analysis.

The largest proportion of the producers in the sample grew wine grape varieties in 1993 (about 80%) followed by raisin, fresh market, and juice grape varieties (about 10% each). However, the proportion of the acreage growing wine grape varieties was lower because farms growing wine varieties tend to be smaller (for example, the sample average size for farms growing wine varieties was about 380 acres compared to almost 2500 acres for farms growing raisin varieties). Similarly, while more than 80% of the 1993 grape acreage was located in California (Table 1A), the percent of the farms located in California is much lower, because grape farms in California are larger that in other states. For example, the sample average grape acreage in California was 3170, while that of New York was 194 and Oregon 41 (Table 1B). For this reason, the proportion of California farms in the sample was only about 20%, similar to that of New York, Michigan, Oregon and Pennsylvania (Table 1B).

It is difficult to provide a general operational definition of IPM since IPM programs are specific to the crop and region for which they are designed and development of IPM programs has not been uniform across pest classes (e.g., insects, plant pathogens, weeds), crops, and regions. Most previous econometric studies have dealt with IPM adoption in general, without further specification of the pest classes that are managed or controlled. While there is merit in keeping the definition general, additional understanding about the barriers to adoption, as well as the effects of IPM, is gained by further characterizing IPM. Thus, this paper considers separately IPM to manage insects and diseases.

In our operational definition of IPM, a farmer is said to have adopted IPM to manage insects (diseases) (i) if the farmer reports having used both scouting for insects (diseases) and economic thresholds in making insecticide (fungicide) treatment decisions, and (ii) the farmer reports the use of one or more additional insect (disease) management practices among those considered to be IPM techniques. Additional IPM techniques included the use of pheromones; use of resistant varieties; alternating pesticides to slow the development of pest resistance to pesticides; adjusting planting dates to lessen pest problems; soil testing for pests; pruning; purchasing beneficial organisms that prey on pests; adjusting application rates, timing, and frequency of pesticide use to protect beneficial organisms; and use of insecticides less harmful to beneficial insects.

The number of insecticide (fungicide) applications per year are used as a measure of pesticide use. The average number of pesticide applications was calculated by dividing the sum (over all active ingredients in the given pesticide class) of the treatment acres by the number of acres treated. Correspondingly, pesticide prices were computed in dollars per insecticide (fungicide) application per acre. Per acre variable profits are defined as per acre revenues (grape prices times yields) minus per acre variable costs (insecticides, fungicides, and associated labor costs).

Unlike simple random sampling, the selection of an individual farm for the survey was not equally likely across all farms on the list because the sample was stratified. Weighted least squares estimation methods were used to correct for bias, with weights equal to the inverse of the probability of selection. The probit equations were estimated separately. Because the errors of the estimating equations for the second stage (Eqs. (1)–(4)) could be correlated, and to gain estimation efficiency, the per acre supply and demand equations were estimated together with the per acre profit function in an iterated Seemingly Unrelated Regression (ITSUR) framework (Zellner, 1962). However, ITSUR techniques were not needed for the probit, because the regressors are the same across all the equations and there are no theoretical restrictions for the regression coefficients (Dwivedi and Srivastava, 1978). The impact of IPM adoption on pesticide use, yields, and farm profits was calculated from Eqs. (1)–(4). For example, the effect of a change in the probability of adoption of insect IPM on insecticide use was calculated from Eq. (3) since $\partial \tilde{X}_1/\partial \boldsymbol{R}_3 = E_{13}$. In elasticity form, the effect of adoption of insect IPM on insecticide use is E_{13} $(\boldsymbol{R}_3/\tilde{X}_1)$. The elasticities reported were calculated at the means.

6. Results

Tables 1B and 2 present a summary of the means of the data for grape farms. Table 1B provides the number of growers in the sample and shows the average extent of adoption of insect IPM and disease IPM, distributed by state. Separate sample averages of selected variables for adopters and nonadopters of IPM for insects and diseases are given in Table 2. For a binary indicator variable, the mean represents the fraction of growers of each group with that

Table 2
Summary of sample averages—U.S. grape producers, 1993

Selected variables	IPM for insects		IPM for diseases	
	Adopters	Nonadopters	Adopters	Nonadopters
YIELD, yield, thousand pounds/acre	8.12	9.44	9.93	7.15
AVRPR, Actual price of grapes, US$/pound	0.33	0.34	0.24	0.32
PAPPLI, insecticide price, US$/acre-per application	29.50	29.86		
PAPPLF, fungicide price, US$/acre-per application			9.84	10.48
PROFIT, Variable profits, thousand US$/acre-year	2.00	1.93	1.88	1.86
SIZE[a]	0.28	0.13	0.32	0.11
INFESI, infestation level, insects[c]	0.09	0.18		
INFESD, infestation level, diseases[c]			0.12	0.21
NAPPLI, Number of insecticide applications/year	1.34	1.39		
NAPPLF, number of fungicide applications/year			2.67	4.43

[a] Dummy variable equal to 1 for larger farms (> 300 acres), 0 otherwise. [b] Dummy variable equal to 1 if farm produces wine grapes, 0 otherwise. [c] Dummy variable equal to 1 if the farmer reports an infestation worse than normal, 0 otherwise.

attribute. For example, the variable SIZE shows that 28% of the adopters of IPM for insects operate large farms (more than 300 acres), more than twice the percentage for nonadopters (13%). In comparison, the continuous variables represent the actual means. For instance, the average annual grape yield obtained by adopters of IPM for diseases is about 9900 pounds per acre, higher than the yield for nonadopters. Table 2 also shows that, on average, adopters of insect IPM use slightly fewer insecticide applications than non adopters, while adopters of IPM for diseases uses 40% fewer fungicide applications than nonadopters.

Table 3
Estimates for adoption, per acre pesticide demand, and supply equations—U.S. grape producers, 1993

Variable	Probit estimates		ITSUR estimates					
	IPM for diseases		Insecticide demand		Fungicide demand		Per acre supply	
	Parameter estimate	Chi-square	Parameter estimate	*t*-value	Parameter estimate	*t*-value	Parameter estimate	*t*-value
INTERCEPT	1.09***	9.98	2.857***	16.81	4.309***	9.88	4.572***	7.60
OFF-FARM W.	−0.002***	13.77	0.000	−0.06	0.002	1.01	−0.003	−0.98
EXPERIENCE	−0.025***	16.32						
EDUCATION	0.758***	22.24						
CONTRACT	−1.082***	48.24						
EXTENSION	−0.083	0.15						
CONSULTANT	−0.127	0.23						4.80
PAPPLF			−0.123***	−4.63	0.038	0.51	−0.008	−1.24
AVPR	−0.003***	45.18	0.013***	4.80	−0.008	−1.24	0.001	0.10
SIZE	0.56***	10.77	0.434**	2.13	2.529***	4.67	−0.950	−1.23
WINE	−0.52***	11.06	0.343**	2.19	0.038	0.09	2.713***	4.60
INFESI			−0.723***	−3.46	4.285***	7.69	−2.722***	−3.46
INFESD			0.360	1.32	−4.501***	−6.19	2.785***	2.63
PROBIPMI[a]			−1.319**	−2.11	0.687	0.41	2.427	1.18
PROBIPMD[a]			−1.484**	−2.35	−3.812**	−2.29	8.615***	4.16
λ_{ins}[b]			0.009	0.03	0.565	0.77	1.614*	1.77
λ_{dis}[b]			−0.326	−0.96	−1.021	−1.14	−2.063*	−1.82
Adjusted R^2	2394[c]***		0.26		0.27		0.22	

[a] Predicted value of probability of adoption of IPM for insects and diseases.
[b] Inverse Mills ratio, IPM for insects and diseases, respectively.
[c] Likelihood ratio.
***, **, *significant at the 1%, 5%, and 10% level.

Regarding the results from the probit regressions, both regressions are highly significant, as measured by likelihood ratio tests (only one probit-regression estimates are shown in Table 3 for lack of space, other results are available upon request). Among the statistically significant variables, the coefficient of the operator's off-farm work activities, measured by the number of off-farm work hours is negative, as expected, confirming that the availability of operator labor has a positive influence on IPM adoption. This corroborates other findings (McNamara et al., 1991; Fernandez-Cornejo et al., 1994) that off-farm employment may present a constraint to IPM adoption, because it competes for on-farm managerial time, as IPM requires a substantial amount of operator's time. Farmer experience is negatively correlated with adoption. This negative sign may be due to the correlation of experience with the age of the operator and would indicate that older farmers are more reluctant to accept newer techniques. Farmer education is positively correlated with adoption, as expected, but use of extension and consultants is not significantly related to IPM adoption. The size variable is positive and significant, confirming other studies that operators of larger farms are more likely to adopt innovations. The type-of-grape dummy is also significantly negative, indicating that wine grape growers are less likely to adopt IPM than table grape producers.

Table 3 also presents the estimated parameters of the insecticide and fungicide demand functions and the per acre supply function. The overall goodness of fit is good for all three equations (adjusted $R^2 = 0.27$), given the cross-sectional nature of the study. The coefficients of the inverse Mills ratios are significant in the supply and profit equations, confirming that self-selection does occur.

Insecticide use is negatively and significantly related to the adoption of insect IPM. Similarly, fungicide use is negatively and significantly related to the adoption of IPM for diseases. The elasticity of pesticide demand with respect to the probability of adoption of the corresponding IPM (calculated at the mean) is -0.26 for the case of insecticides and -0.10 for fungicides (Table 4). That is, a 10% increase in the probability of adoption of IPM for insects would decrease the number of insecticide applications by nearly 3% and a 10% increase in the probability of adoption of IPM for diseases would decrease the number of fungicide applications by 1%.

Table 4
The impact of IPM adoption for grape producers—U.S. grape producers, 1993

	Elasticity with respect to probability of IPM adoption
Elasticity of pesticide use with respect to	
IPM for insects	−0.26
IPM for diseases	−0.10
Elasticity of yields with respect to	
IPM for insects	ns
IPM for diseases	0.30
Elasticity of farm profits with respect to	
IPM for insects	ns
IPM for diseases	0.39

ns: standard error was too large; the underlying regression coefficient was not significant.

Table 3 also shows that the impact of IPM on yields is positive for both insect and disease IPM, although this effect is not significant for insect IPM. About a third of the ITSUR parameter estimates for the profit function (not shown but available upon request) are significant at the 1% level. The effect of IPM adoption on profits is positive but only significant for IPM for diseases: the elasticity of variable farm profits with respect to the probability of adoption of IPM for diseases is 0.39 (Table 4). This result means that an increase of 10% in the probability of adoption of IPM for diseases would increase variable profits by almost 4%.

Our results are consistent with those of Hall (1977) in that IPM reduced pesticide use. However, the empirical evidence on the effect of IPM on pesticide use is mixed, even for a given crop. Among econometric studies, Burrows (1983) found that IPM adoption lead to a significant reduction in pesticide expenditures for a sample of California cotton growers, but Carlson (1980) cites evidence of "both complementary and substitute relationships between scouting and pesticide use" among cotton producers in North Carolina, and Wetzstein et al. (1985) found that "IPM has no effect on pesticide expenditures" among a sample of Georgia cotton farmers. There is little econometric results on the impact of IPM among fruit producers (Norton and Mullen, 1994); Fernandez-Cornejo and Jans (1996) found that IPM did not have a significant effect on insecticide use for a sample of orange producers in California and Florida.

Having determined that IPM reduces overall pesticide use for grape growers, we also examine the impact of IPM on major pesticide active ingredients. We focus on 11 active ingredients which represent more than 90% of the insecticides and fungicides used on grapes. As shown in Table 5, on the average, adopters of insect IPM use fewer applications of two of the three major insecticides listed and adopters of disease IPM use fewer applications of six of the eight major fungicides.

The overall index of human (mammal) toxicity (LTI) encompassing both acute and chronic effects is also calculated for each of the 11 ingredients and shown in Table 5. In addition, a weighted average toxicity index is calculated, where the weights are based on the area treated, application rate, and number of applications. As it can be seen at the bottom of Table 5, the average toxicity of the insecticides used by adopters of insect IPM is slightly lower (LTI = 1.7) than that of nonadopters (LTI = 1.8); both of these toxicities are considered as moderate. The toxicity of fungicides used is essentially the same for adopters and nonadopters of IPM for diseases and in both cases the average toxicity of fungicides is quite low (LTI = 0.35). However, the fungicide results are strongly influenced by sulfur, which has a large weight because it is intensively used in grape production. Sulfur has a low mammal toxicity (LTI = 0.33).

To examine the environmental impact of IPM we use the environmental impact quotient (EIQ) (Kovach et al., 1992). As indicated earlier, the EIQ measures the impact of each pesticide active ingredient on human health and the environment. Table 5 provides the EIQ values of the active ingredients used in grape production. We also calculate an overall weighted average EIQ for the major insecticides and fungicides used. Weights are based on the area treated, application rates, and number of applications (Table 5). As seen at the bottom of Table 5, the overall EIQ of insecticides decreases slightly for adopters of insect IPM (from 25.2 to 24.7) but the

Table 5
Major pesticides used, toxicity, and environmental impact quotient—U.S. grape producers, 1993

Active ingredient (class)	Area applied[a], %	Application rate[a], Lb/acre	Overall toxicity index, LTI	Environmental impact quotient[b], EIQ	IPM for insects		IPM for diseases	
					Adopters	Nonadopters	Adopters	Nonadopters
					Number of applications per year			
Captan, (fungicide)	3	1.83	3.00	28.6			1.65	2.54
Carbaryl, (insecticide)	7	1.61	3.67	22.6	1.04	1.16		
Cryolite (insecticide)	35	5.32	1.33	21.4	1.67	1.53		
Copper hydroxide (fungicide)	9	0.64	2.67	33.3			1.10	1.52
Copper oxychl. sul. (fungicide)	4	2.62	0.33	25.0[c]			1.34	1.54
Fenarimol (fungicide)	39	0.03	2.67	27.3			1.51	2.06
Mancozeb(fungicide)	11	1.98	1.00	62.3			2.10	1.70
Myclobutanil (fungicide)	33	0.10	1.66	41.2			2.18	1.76
Propargite (insecticide)	32	1.54	3.33	42.7	1.18	1.31		
Sulfur (fungicide)	82	9.64	0.33	45.5			4.89	6.19
Triadimefon (fungicide)	11	0.12	1.00	33.3			1.07	1.93
Average toxicity index (LTI) for insecticides					1.71	1.77		
Average toxicity index (LTI) for fungicides							0.35	0.35
Average EIQ for insecticides					24.69	25.24		
Average EIQ for fungicides							45.6	45.6

[a] From USDA (1994).
[b] EIQ values for individual active ingredients are from Kovach et al. (1992)
[c] Estimated (not included in Kovach et al., 1992)

overall EIQ of fungicides remains the same (at about 45.5) for adopters and nonadopters of IPM for diseases.

7. Concluding comments

This paper presents a methodology to calculate the impact of IPM on pesticide use, toxicity and other environmental characteristics of the pesticides, crop yields, and farm profits. The methodology is applied to the case of grape producers in six states accounting for most of the U.S. production. The method is generally applicable to technology adoption. It accounts for self-selectivity and simultaneity, and the pesticide demand and yield equations are theoretically consistent with a restricted profit function.

The results support the notion that, among grape growers, adopters of IPM for insects and IPM for diseases use significantly fewer insecticide and fungicide applications than do nonadopters. In addition, both average toxicity and the environmental impact quotient decreases slightly with adoption of insect IPM, but they remain about the same for adopters and nonadopters of IPM for diseases. The effect of IPM adoption on yields and variable profits is positive but only significant for the case of IPM for diseases, i.e., the adoption of IPM for diseases increases yields and profits significantly. Other important determinants of pesticide demand, besides IPM adoption, are pesticide prices, grape prices, pest infestation levels, type of grape, operator off-farm work, and farm size.

Two limitations of the study are the incomplete modeling of the substitution possibilities between pesticides and other purchased inputs, particularly fertilizers, and the exclusion of production risk. In the first case, the limitations are attributable to the lack of price input data for some inputs. Panel data would be needed to address the second issue satisfactorily. When better data become available, these limitations will be surmounted helping improve our understanding of technology adoption in agriculture.

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