The Environmental Effects of Adopting IPM Techniques: The Case of Peach Producers

Jorge Fernandez-Cornejo and Jennifer Ferraioli

ABSTRACT

The impact of adopting integrated pest management (IPM) techniques is examined for peach producers in eight states accounting for most of the U.S. production. The method accounts for self-selectivity, simultaneity, and the pesticide demand equations are theoretically consistent with a restricted-profit function. Biological pest management techniques tend to reduce pesticide use and pesticide toxicity substantially, while pesticide-efficiency techniques (using scouting and economic thresholds) have an increasing effect on pesticide use and toxicity, and cultural techniques have an insignificant effect on pesticide use and toxicity.

Key Words: *biological techniques, cultural techniques, integrated pest management, peach production, pesticide use, self-selection, toxicity.*

Despite the positive effect of pesticide use on agricultural productivity, the potential hazard of pesticide exposure to human health and the environment has caused increased concern. 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 pesticide use and reduce the associated health and environmental risks and set the goal of "developing and implementing IPM programs for 75 percent of the total crop acreage" by the year 2000 (Browner *et al.*).

Integrated Pest Management (IPM) in-

Jorge Fernandez-Cornejo and Jennifer Ferraioli are with the Economic Research Service, U.S. Department of Agriculture, 1800 M Street, Room 4052, Washington, DC 20036-5831. The authors would like to thank two anonymous reviewers for helpful comments. The views expressed are those of the authors and do not necessarily correspond to the views or policies of the U.S. Department of Agriculture.

cludes an assortment of techniques or practices developed to address some of the health and environmental concerns of pesticide use and the problem of pest resistance to pesticides (OTA). However, the set of practices that would meet production and environmental goals differs by crop, region, and pest problems. IPM techniques are designed to limit pest infestation at an economically acceptable level rather than attempting to completely eradicate all pests. In general terms, IPM has been defined as "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). The active encouragement of IPM adoption by government agencies, agricultural extension services, consumer groups,

and environmental organizations, foreshadows the increasing importance of IPM techniques in coming years.

The adoption of IPM techniques has been analyzed by several researchers (see review in Norton and Mullen) but there are few farm-level econometric studies on the effect of IPM on pesticide use (Burrows; Hall and Duncan; Wetzstein *et al.*; Fernandez-Cornejo 1996, 1998). IPM studies are recently focusing on fruit and vegetable production because this production is particularly intensive in pesticide use. Per-acre expenditures on pesticides by fruit and vegetable growers are nearly seven times the agricultural average (Fernandez-Cornejo *et al.*) In addition, concerns about pesticide residues are especially important in fruits and vegetables, often consumed with little postharvest processing. Among fruits, most research has concentrated on apples (Norton and Mullen) and a few studies examine oranges (Fernandez-Cornejo and Jans 1996) and grapes (Fernandez-Cornejo 1998) but no studies on the impact of IPM on peach production have been published.

Assessing and comparing the effects of IPM programs is difficult because of the heterogeneity of the data across regions, time, pest classes (insects, plant pathogens, weeds), and types of crops grown. Moreover, IPM involves a number of techniques which have been developed at different degrees for different crops, pest classes, and regions, and farmers may adopt IPM at different degrees.

Although sometimes IPM is defined as an attempt to reduce pesticide use while maintaining current production levels (Hall), the empirical evidence on the effect of IPM on pesticide use is mixed, even for a given crop. Some econometric studies find that IPM adoption leads to a significant reduction in pesticide use (Burrows; Fernandez-Cornejo 1996, 1998), others find an increase (Yee and Ferguson), and still others find no significant effect (Wetzstein *et al.*; Fernandez-Cornejo and Jans 1996).

To a large extent, empirical results on the impact of IPM on pesticide use may not be uniform because of differences in the operational definition of IPM, particularly the prac-

tices considered in the IPM "bundle." For example, scouting appears to increase pesticide use in many cases studies (Norton and Mullen). In the case of cotton, the commodity most studied in relation to IPM, pesticide use is found to increase with the adoption of scouting in most of the cases that examine the effect of scouting separately (Norton and Mullen; Yee and Ferguson). However, when scouting is examined together with other IPM techniques, the combination is often found to decrease pesticide use (Norton and Mullen).

Despite these interesting results, no systematic effort has been made to measure the effect of different types of IPM techniques on pesticide use in U.S. agriculture. For this reason, this paper presents a framework to examine the impact of adopting bundles of major pest management techniques on pesticide use. In addition, the paper uses a farm-level survey data for peach growers to calculate the impact of each of these bundles on pesticide use, toxicity, and selected environmental characteristics.

Pest Management Techniques and IPM

Following USDA (1997a, p.189) this paper classifies pest-management techniques into three broad groups. The first group or bundle consists of techniques to improve the efficiency of chemical pesticide use. It includes scouting, the use of economic thresholds, and alternating pesticides to slow the development of pest resistance to pesticides. These techniques, while relying on pesticides, may reduce risks by using less toxic materials, lower rates, or lower number of applications (USDA 1997a, p.189) and can reduce the amount of residues available for transport to the environment. Scouting involves the regular and systematic sampling of the fields to estimate pest infestation levels and subsequently determine if an economic threshold (at which net economic losses are avoided) is reached (Vandeman *et al.*) and, thus, decide the application of a control strategy.

The second group includes a number of cultural techniques and practices for fruit production, such as pruning, field sanitation, and till-

age. The third group consists of biological techniques including what is commonly known as *biological controls,* which until the 1980s was generally restricted to the action of natural enemies of pests, such as predators, parasitoids, and pathogens (Sailer, p.9). More recently, the concept of biological control has expanded and often includes biological pesticides or biopesticides, including bacteria, viruses, and fungi (Sailer, p.9). Among biopesticides, the most successful so far is the soil bacterium *Bacillus thuringiensis* (Bt). Bts are microbial insecticides which kill insects by lethal infection. The use of Bt is increasing, particularly in IPM programs, because of the positive impact of the bacterium on environmental safety, performance, cost competitiveness, selectivity, and activity on lepidopteran insects (Marrone). Other biological pest management techniques include the use of semiochemicals, including pheromones and feeding attractants to monitor insect populations and to control them by disrupting mating, and genetic controls including the use of varieties/rootstocks resistant to some diseases or insects.

Toxicity and the Environmental Impact of Pesticide Use

While important, the total amount of pesticide use is just one element in determining the potential risk of pesticide use. In particular, there has been little empirical examination of the claims of many IPM programs that pesticides used in IPM differ from those used on a preventative or routine schedule and that IPM uses pesticides that target specific pests and are less toxic to beneficial organisms (Allen *et al.*). One step towards bridging this gap is to consider separately the impact of IPM by pesticide class (e.g., insecticides, fungicides) as well as by major pesticide category, e.g., synthetic and naturally-occurring (nonsynthetic) pesticides, which have widely different toxicities.[1]

Human toxicity is usually inferred from experimental data on mammalian toxicity. Two categories of mammalian toxicity are usually considered. Acute toxicity is the capacity of a substance "to cause poisonous effects resulting in severe biological harm or death soon after a single exposure or dose" (*Farm Chemicals Handbook*), the exposure usually lasting no more than a day. Some common measures of acute toxicity are the LD_{50} (lethal dose) values which measure the amount or dose in milligrams of toxicant per kilogram of body weight necessary to kill 50 percent of the test animals within the first 30 days following exposure. The EPA uses three LD_{50} measures of acute mammalian toxicities depending on whether the toxic material is ingested by mouth (oral LD_{50}), inhaled (inhalation LD_{50}), or absorbed by contact with the skin (dermal LD_{50}).[2] The EPA uses four acute toxicity categories: the more toxic (Category I) is assigned the signal word "danger" on the pesticide label and the least toxic corresponds to Category IV and is assigned the signal word "caution."

Chronic toxicity usually refers to the ability of a substance to cause poisonous health effects after a long-term, low-level exposure (Cohrsen and Covello, p.358). Chronic toxicity includes long-lasting or permanent damage from one exposure, continuing exposure, cumulative effects on the body, or effects that appear long after the original exposure. Chronic toxicity includes carcinogenicity (capability of producing cancer—malignant tumors—in animals or in humans), mutagenicity (ability to induce genetic changes in living cells), teratogenicity (capability of producing developmental malformations, monstrosities, or serious deviations from normality). The EPA also uses a chronic toxicity scale of carcinogenicity, in which substances are divided into six categories, ranging from "human carcinogen" to "evidence of noncarcinogenicity for humans," following a "weight of evidence"

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[1] Toxicity is defined in a general sense as the "quality or degree of being poisonous or harmful to plant, animal, or human life" (Cohrssen and Covello, p.374).

[2] The EPA uses two additional measures: eye effects (corrosiveness, cornea opacity, and irritation) and skin effects (corrosiveness and irritation).

characterization (*Farm Chemicals Handbook,* p.C72).

Several methods have been proposed to summarize the toxicity of pesticides by expressing it as an overall index, but there is no consensus about the scales and the weights assigned to the various components of the index. This paper uses the overall index of human toxicity proposed by Fernandez-Cornejo and Jans (1995). This toxicity 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 measures of acute toxicity considered by the EPA. LAI is set 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 similar to EPA's carcinogenicity classification in that it is based on the weight of the evidence. Thus LCI is assigned a decreasing score for weaker indications of potential carcinogenicity. Following Hammitt, 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 it is reported to be mutagenic (produces genetic changes in living cells indicating potential carcinogenicity) or produces other chronic effects not included elsewhere. Finally, the LTI component is defined to be equal to 4 if the pesticide is teratogenic.

The potential impact of pesticides on human health and the environment is summarized by using the Environmental Impact Quotient (Kovach). The EIQ has three components based on the three potentially affected elements of agricultural production systems: the farm worker (applicator and picker), the consumer (directly and through the groundwater), and the ecology (including fish, birds, bees, beneficial organisms, and plants). 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 farm worker component includes acute and chronic elements and is calculated from mammal toxicity and persistence. The consumer component is based on chronic toxicity, persistence, and systemicity (to account for ability of a pesticide to be absorbed by the plant). The ecological component is calculated from fish, bird, bee, and beneficial arthropod toxicity; persistence; and leaching and surface loss potential.

Pesticide Use in Peach Production

Peaches were one of the top five U.S. fruit crops in terms of acreage (173,000) and value of production ($380 million) in 1996 (USDA 1997b, pp.11–14). Peach production in the U.S. uses relatively large amounts of a variety of pesticides. As Table 1 shows, both insecticides and fungicides are applied to 97 percent of the acreage devoted to peach production (herbicides are used on 66 percent of the acreage, and other chemicals on 5 percent). Moreover the amount of herbicides used is less than 10 percent of the amounts of insecticides or fungicides used.

Nonsynthetic petroleum distillate is the most extensively used insecticide with 1.5 million pounds per year applied over 33 percent of the acreage, followed by synthetic methyl parathion (165,000 pounds applied on 50 percent of the acres), and Diazinon (83,000 pounds on 21 percent of the acres). Commercial bioinsecticides based on the bacterium *Bacillus Thuringiensis* (Bt) are only used on 5 percent of the acres (Table 2). Nonsynthetic sulfur is the top fungicide with four million pounds per year applied over 74 percent of the peach acreage, followed by synthetic captan with 257,000 pounds applied over 31 percent of the acres, chlorothalonil (147,000 pounds over 34 percent of the acres), and ziram (131,000 pounds over 15 percent). Copper hydroxide was applied in the amount of 97,000 pounds over 14 percent (Table 2).[3]

Table 2 shows the overall toxicity index

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[3] Herbicide use is quite small in peach production, totaling 182,000 pounds per year and will not be included in the analysis.

Table 1. States Included in the Survey and Areas Receiving Pesticides[1]

| State | Bearing Acreage[2] | Percent of Planted Acres Treated and Total Applied | | | | | |
| | | Insecticides | | Fungicides | | Herbicides | |
		%	1000 lbs	%	1000 lbs	%	1000 lbs
California	72,600	96	1,623	95	1,547	66	81
Georgia	21,000	100	71	100	1,055	95	30
Michigan	5,500	100	25	100	160	56	7
New Jersey	10,800	99	59	99	759	77	18
New York	1,600	88	10	94	30	51	2
Pennsylvania	6,800	100	40	100	179	52	11
South Carolina	23,000	100	120	100	1,275	45	29
Washington	2,500	96	74	85	25	50	5
Total	143,800	97	2,123	97	5,029	66	182

[1] Areas exclude methyl bromide (used only in 8% of California acreage).
[2] Acreage in California includes nonbearing acres.
Source: USDA, 1996, p. 111.

(LTI) calculated for each of the major pesticides used by peach growers as well as the weighted average toxicity index for synthetic and nonsynthetic pesticides, where the weights are based on the area treated, application rate, and number of applications. As can be seen in Table 2, the average toxicity of the synthetic insecticides used (2.34) is much higher than that of nonsynthetic insecticides (0.33). This is also the case for fungicides.

In addition, Table 2 provides the Environmental Impact Quotient (EIQ) values of the major pesticides used in peach production as well as the overall weighted average EIQ for synthetic and nonsynthetic pesticides. The weights are based on the area treated, application rates, and number of applications (Table 2). The overall EIQ for synthetic insecticides (3·.8) is higher than the EIQ of nonsynthetic insecticides (27.5) but the EIQ of synthetic fungicides is smaller than that of nonsynthetic fungicides, because of the very high EIQ assigned to sulfur by this method. While sulfur is relatively nontoxic to humans and mammals, its high EIQ is due to its toxicity to beneficial insects.

The Theoretical Framework

This section discusses the theoretical model used to analyze the impact of major categories (bundles) of pest management techniques on

pesticide use. Three theoretical issues must be considered to develop the model. First, the model must take into consideration that farmers' adoption decisions and pesticide use may be simultaneous, due to unmeasured variables correlated with both adoption and pesticide demand such as the size of the pest population, pest resistance, farm location, and grower perceptions about pest control methods (Burrows). In addition, the model must correct for self-selectivity to prevent biasing the results (Greene). Self-selection arises because farmers are not assigned randomly to the two groups (adopters and nonadopters), but they make the adoption choices themselves. Therefore, adopters and nonadopters may be systematically different and these differences may manifest themselves in farm performance and could be confounded with differences due purely to adoption. Finally, the model must ensure that the pesticide demand functions are consistent with farmers' optimization behavior, i.e., profit maximization, since the demand for pesticidal inputs is a derived demand.

Modeling the Adoption Decision

The adoption of a new technology is essentially a choice between two alternatives, the conventional technology and the new one. As such, choice models developed in consumer theory have been used to motivate adoption

Table 2. Major Pesticides Used, Toxicity, and Environmental Impact, U.S. Peach Producers, 1995

	Area Applied %	Application Rate lb/acre	Number of Appli- cations	Total Applied Thousand Pounds	Acute Toxicity EPA Category	Overall Toxicity Index (LTI)	Environ- mental Impact Quotient (EIQ)
Insecticides[1]							
Synthetic insecticides							
Azinphos-methyl	20	0.46	4.0	51.6	I	2.67	43.1
Carbaryl	8	1.93	1.5	34.6	I/II	3.67	22.6
Chlorpyrifos	17	1.34	1.3	41.4	II/III	2.50	52.8
Diazinon	21	2.28	1.2	82.7	II/III	2.67	34.2
Endosulfan	6	0.99	2.8	24.5	I	3.33	40.5
Methyl parathion	50	0.54	4.2	165.4	I	1.50	35.2
Phosmet	11	1.11	2.1	38.7	II	2.50	23.9
Propargite	11	1.57	1.1	27.9	I	3.33	42.7
Major synthetic in- secticides				466.8		2.34	36.8
Nonsynthetic insecticides							
Petroleum distillate	33	26.73	1.2	1497.0	IV	0.33	27.5
Major nonsynthetic insecticides				1497.0		0.33	27.5
All insecticides	97			2022.52			28.9
Fungicides							
Synthetic fungicides							
Benomyl	13	.53	1.6	15.8	IV	1.67	69.5
Captan	31	1.69	3.4	256.8	I/II	3.00	28.6
Chlorothalonil	34	2.14	1.4	146.7	I/II	2.67	46.0
Iprodione	40	.66	1.3	49.1	IV	1.00	26.6
Ziram	15	5.18	1.1	131.4	III	2.00	N/A
Major synthetic fungicides				599.8		2.46	35.2
Nonsynthetic fungicides							
Copper hydroxide	14	3.80	1.3	96.5	I	2.67	33.0
Copper oxide	7	5.42	1.0	57.6	II	0.67	N/A
Sulfur	74	8.06	4.7	4018.0	IV	0.33	45.5
Major nonsynthetic fungicides				4172.1		0.39	45.2
All fungicides	97			5028.7[3]			41.7

[1] *Bt (Bacillus thuringensis)* was used on 5% of the acres with an average of 1.5 applications. However, quantity and application rate were not reported because, unlike all other pesticides, *Bt* is not expressed in weight units.
[2] Includes minor insecticides not listed.
[3] Includes minor fungicides not listed.
Sources: Columns 1–4, USDA, 1996; column 5, *Farm Chemical Handbook*; column 7, Kovach *et al.*

decision models. In this context, growers are assumed to make their decisions by choosing the alternative that maximizes their perceived utility. Thus, grower i is likely to adopt a tech- nology if the utility of adopting, U_{i1}, is larger than the utility of not adopting, U_{i0}. However, only the binary random variable I (taking the value of 1 if the technology is adopted and 0

otherwise) is observed, as utility is not known to the analyst with certainty and is treated as a random variable (Ben-Akiva and Lerman). Thus: $U_{ij} = V_{ij} + e_{ij}$, 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 distributed normally, then their difference will also be normally distributed and the probit transformation can be used to model the farmer's adoption decision (Fernandez-Cornejo 1996, 1998). Thus, the probability of adoption of bundle k of pest management techniques is $P(\mathbf{I}_k = 1) = F(\gamma_k' \mathbf{Z}_K)$, where the binary variable $\mathbf{I}_k$ denotes the adoption of the kth bundle, F indicates the cumulative normal distribution, and $\mathbf{Z}_k$ is the vector of explanatory variables, which include the factors or attributes that influence adoption. The variables included in $\mathbf{Z}_k$ are product price, regional (state) dummies, farm size, farmer's education and experience, and contractual arrangements for the production/marketing of the product.

As Griliches showed, expected profitability positively influences the adoption of agricultural innovations. In consequence, factors expected to increase profitability by increasing revenues or reducing costs are also generally expected to positively influence IPM adoption. Given that an objective of pest management in agriculture is to reduce crop yield losses, there is a higher incentive to reduce these losses for high-value crops. However, sometimes IPM is at odds with a grower's need to control cosmetic damage (Kovach and Tette). In these cases, a negative correlation between IPM adoption and product quality could translate into a negative correlation between IPM and product price.

The physical environment of the farm may affect profitability directly through increased fertility, and indirectly through its influence on pests. Thus, it is plausible that a farm located in an adequately wet, fertile area is more likely to adopt IPM than a farm located in an infertile region. While weather, soil type, and other locational variables may affect the adoption decision, degrees of freedom and collinearity considerations often limit their use in a regression context. For this reason, dummy variables for states or for regions are often used as locational proxies.

IPM adoption may also vary among crops and regions because of differences in the availability of reliable IPM techniques. Like most technological innovations, IPM techniques are the product of research and development programs funded by the public and private sectors. These programs may differ across crops and regions mainly due to differences in research funding and effort.

Other factors that have been empirically found to have a significant influence on IPM adoption in previous studies may be in fact proxies for managerial ability. Among these factors are the following:

(i) *Farm size*: Adoption is expected to take place earlier on larger farms than on smaller farms (Fernandez-Cornejo *et al.* 1994; Just, Zilberman, and Rauser 1980). However, farm size is likely to be a surrogate for other factors, such as wealth and access to credit, managerial ability, information, or scarce inputs (Feder, Just, and Zilberman 1985).

(ii) *Education and age*: Adoption is believed to be positively associated to farmer characteristics that are believed to be correlated to managerial ability, particularly the operator's ability to process information, such as education and experience. IPM is a complex, knowledge- and information-intensive technology: 49 percent of Iowa farmers acquainted with IPM thought that it was complicated and difficult to use (Bultena). Empirically, Kovach and Tette 1988; Harper *et al.* 1990; and Fernandez-Cornejo *et al.* 1994 have found IPM adopters to be younger and more educated.

(iii) *Contracts that influence managerial decisions*: For example, a production contract between a grower and a processor usually specifies the acreage to be grown or quantity and quality of product to be delivered, as well as production practices, including pest management.

Modeling the Impact of Adoption

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. Simultaneity and self-selectivity are accounted for by expanding Heckman's procedure. First, the usual probit analysis is used to estimate the parameters γ_k of the adoption decision equations. The inverse Mills ratio λ_k is also estimated for each observation (Greene). Second, because the variable I_k is endogenous, the predicted probabilities (from the probit equations) are used as instrumental variables for I_k. Third, the λ_k's are appended as additional regressors to the supply, demand, and profit equations.

The restricted profit function (Diewert) is used to estimate theoretically consistent supply, demand, and profit equations. The theory of the restricted profit function is well developed and its framework is general enough to accommodate as special cases cost and revenue functions and all possible intermediate cases. The profit function is used to capture the information about the production structure, assuming profit-maximizing producers are operating in competitive markets.

The restricted profit function is defined by $\pi(\mathbf{p}, \mathbf{w}, \mathbf{s}, \mathbf{R}) = \mathrm{Max}_{XY}(\mathbf{p'y} - \mathbf{w'x}; \mathbf{x}, \mathbf{y} \in T)$, where $\mathbf{y}$ is the vector of outputs, $\mathbf{x}$ is the vector of variable inputs, $\mathbf{s}$ the vector of nonnegative quasi-fixed inputs, $\mathbf{R}$ the vector of other factors such as locational or weather proxies; $\mathbf{p}$ is the price vector of outputs, $\mathbf{w}$ is the price vector of variable inputs, and T is the production possibilities set, assumed to be a 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). 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 $\pi(\mathbf{p}, \mathbf{w}, L, \mathbf{R}) = L \cdot \tilde{\pi}(\mathbf{p}, \mathbf{w}, \mathbf{R})$, where $\tilde{\pi}$ is the per-acre profit function: $\tilde{\pi} = \mathrm{Max}_{\tilde{y}\tilde{x}}(\mathbf{p'\tilde{y}} - \mathbf{w'\tilde{x}})$ and $\tilde{\mathbf{y}} = \mathbf{y}/L$, $\tilde{\mathbf{x}} = \mathbf{x}/L$ are the per-acre output and input quantity vectors (Fernandez-Cornejo 1996, 1998). By Hotelling-Shephard's lemma, the per-acre output supply and input demand

functions are then given by $\tilde{\mathbf{y}} = \partial\tilde{\pi}(\cdot)/\partial\mathbf{p}$ and $\tilde{\mathbf{x}} = -\partial\tilde{\pi}(\cdot)/\partial\mathbf{w}$.

For the empirical estimation, we use a normalized quadratic restricted profit function (Diewert and Ostensoe; Fernandez-Cornejo 1996, 1998), considering land as a fixed input, a single output (peaches), using the price of labor as the numeraire, and appending the inverse Mills ratio terms as an additional regressor, as well as disturbance terms, the per-acre supply function ($\tilde{\mathbf{y}}$), the per-acre pesticide demand function (vector $\tilde{\mathbf{x}}$ with four components for synthetic insecticides, synthetic fungicides, nonsynthetic insecticides, and nonsynthetic fungicides), and the per-acre profit function ($\tilde{\pi}$) become (Fernandez-Cornejo 1996, 1998):

(1) $\quad \tilde{y} = \mathbf{a} + Hp + \sum_j G_j w_j + \sum_k F_k R_k + \theta_y \lambda + \epsilon_y$

(2) $\quad \tilde{x} = b_1 + G_{11}p + \sum_j B_{1j}w_j + \sum_k E_{1k}R_k$

$\qquad\qquad + \theta_x \lambda + \epsilon_x$

(3) $\quad \tilde{\pi} = a_0 + ap + \sum_j b_j w_j + \sum_k c_k R_k + Hp^2$

$\qquad\qquad + \sum_j G_{1j}pw_j + \sum_k F_{1k}pR_k$

$\qquad\qquad + \sum_j \sum_i B_{ij}w_i w_j + \sum_k \sum_j E_{jk}w_j R_k$

$\qquad\qquad + \sum_j C_{ik}R_i R_k + \theta_\pi \lambda + \epsilon_\pi$

here now $\mathbf{p}$ and $\mathbf{w}$ are the output and input prices, a, H, E_{jk}, F_k and G_{1j} are parameters. The vector $\mathbf{R}$ includes farm size (R_1), proxies for insect and disease infestation levels $(R_2$ and $R_3)$, and the predicted probabilities of adoption obtained from the probit model $(R_4$, R_5, and R_6 for pesticide-efficiency, biological, and cultural practices). For example, the demand function for synthetic insecticides becomes, from (2):

$\tilde{x}_1 = b1 + G_{11}p + B_{11}w_1 + B_{12}w_2 + B_{13}w$

$\qquad + B_{14}w_4 + E_{11}R_1 + E_{12}R_2 + E_{13}R_3$

$\qquad + E_{14}R_4 + E_{15}R_5 + E_{16}R_6 + \theta_x\lambda + \epsilon_x$

Economic theory requires the restricted profit function to be convex in prices and con-

cave in quasi-fixed factors. Convexity in prices implies that the Marshallian elasticities are of the "correct" sign; i.e., the coefficient of the output price of the supply function must be positive while the coefficients of the own-price demand functions must be negative. For example, we expect the coefficient B_{11} of the price of synthetic pesticides in the demand function of synthetic pesticides to be negative. Regarding the cross price coefficients there is no "a priori" restriction for the sign of the coefficients because those signs depend on whether the pair inputs in question are substitutes or complements. There are no theoretical restrictions regarding the signs of the coefficients of the other factors (vectors **E** and **F**).

Data and Model Estimation

The data are obtained from the Agricultural Chemical Use Survey and its Economic Follow-On for fruits, administered between the fall of 1995 and the spring of 1996 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 with at least an acre of production. The survey includes fresh market and processing peach crops grown in California, Georgia, Michigan, New Jersey, New York, Pennsylvania, South Carolina, and Washington, covering 144,000 acres and accounting for most of the U.S. acreage (Table 1). After observations with missing values were excluded, 507 usable observations of peach-producing farms are available for analysis.

The three bundles of pest management techniques considered in this study are (i) pesticide-efficiency techniques including scouting, use of economic thresholds, and alternating pesticides to slow the development of pesticide resistance to pests; (ii) cultural techniques and practices including pruning, field sanitation, and tillage; and (iii) biological management techniques including protection of beneficial organisms by adjusting application rates, timing, and frequency of insecticide use; purchasing or releasing beneficials, using

pheromones for monitoring or control; use of Bt; and host plant resistance techniques (use of insect and using resistant varieties/rootstocks) which are critical for peaches because they are very susceptible to diseases and nematodes (Harper and Greene).

The impact of pest management bundles and the overall effect of IPM on pesticide use is measured separately (but estimated simultaneously) for synthetic and nonsynthetic (mostly petroleum oils) insecticides and synthetic and nonsynthetic (mostly sulfur) fungicides. The number of pesticide applications per year are used as a measure of pesticide use.[4] Correspondingly, dollars per application per acre are used as pesticide price. Variable profits are defined as per-acre revenues (peach prices times yields) minus per-acre variable costs (pesticide and associated labor costs).

Unlike simple random sampling, the selection of an individual farm for the survey is not equally likely across all farms on the list because the sample was stratified. Weighted least squares estimation methods are used to correct for bias, and the weights are equal to the inverse of the probability of selection. The probit equations are estimated separately, as seemingly unrelated regression (SUR) techniques are not necessary because the regressors are the same across all the equations and there are no theoretical restrictions for the regression coefficients (Dwivedi and Srivastava). However, the errors of the estimating equations for the second stage (equations 1–3) are likely to be correlated; thus, to gain estimation efficiency, the per-acre supply and demand equations are estimated together with the per-acre profit function in an iterated seemingly unrelated regression (ITSUR) framework (Zellner). The impact of adoption on pesticide use is calculated from equations (2). For example, the impact of biological practices on synthetic insecticide use is $\partial \tilde{x}_1 / \partial R_5 = E_{15}$.

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[4] The average number of pesticide applications is calculated by dividing the sum (over all active ingredients in the given pesticide class) of the treatment acres by the number of acres treated. Thus the number of applications may be any positive number, not necessarily an integer.

Table 3. Probit Estimates for Adoption, Peach Producers, 1995 (standard errors in parentheses)

Variable	Biological Techniques		Pesticide-efficiency Techniques		Cultural Techniques	
	Parameter Estimates	Chi-square[7]	Parameter Estimates	Chi-square[7]	Parameter Estimates	Chi-square[7]
Intercept	1.356*** (0.249)	29.57	−0.302 (0.236)	1.64	−0.051 (0.228)	0.05
Z_1 Education[1]	−0.245* (0.139)	3.13	0.162 (0.131)	1.51	0.022 (0.126)	0.03
Z_2 Grew up on farm[2]	0.122 (0.165)	0.54	−0.389** (0.154)	6.34	−0.179 (0.155)	1.35
Z_3 Contract[3]	0.084 (0.193)	0.19	−0.390* (0.206)	3.58	0.181 (0.188)	0.92
Z_4 California[4]	1.150*** (0.193)	35.65	0.357* (0.202)	3.13	0.010 (0.188)	0.00
Z_5 Size[5]	0.301** (0.128)	5.53	0.197 (0.128)	2.38	−0.170 (0.120)	1.99
Z_6 Price[6]	0.001** (0.0007)	3.98	−0.001 (0.0007)	2.20	0.002*** (0.0007)	12.24
Log of the likelihood ratio	1691***		1785***		2036***	

[1] Dummy variable for education (1 if completed high school or vocational training, 0 otherwise).
[2] Dummy variable equal to 1 if operation grew up on farm, 0 otherwise.
[3] Dummy variable equal to 1 if farm sells its own output under a production or marketing contract, 0 otherwise.
[4] Dummy variable equal to 1 if farm is located in California, 0 otherwise.
[5] Dummy variable equal to 1 for larger farms (> 150 acres), 0 otherwise.
[6] Actual price of fresh peaches, $/pound.
[7] Statistic used to test the significance of the coefficients of the probit equation.
***, **, * significant at the 1-percent, 5-percent, and 10-percent level.

Model Results

Table 3 presents the results from the probit regressions. All three regressions are highly significant, as measured by the likelihood ratios. Among the significant variables, the coefficient of the size variable is positive for the biological techniques corroborating our expectation that operators of larger farms are more likely to adopt innovations. Average price of the crop is also positively correlated with adoption of biological and cultural techniques, as expected. The dummy variable for high school education is negatively related to the adoption of biological techniques, also as expected given that the base case (the rest of the sample) consists essentially of operators with some college or completed college education. Farms with production or marketing contracts tend to have a significantly decreased probability of adoption of pesticide efficiency techniques while increasing the probability of adoption of biological and cultural technique, although this increase is not statistically significant. The regional (California) dummy is also significantly positive, indicating that California peach growers are more likely to adopt biological and chemical-efficiency techniques than those of other states. IPM adoption in California may be due to the more favorable physical environment (e.g., fertility) of the farms located in this state as well as the greater availability of reliable IPM techniques in this state due to its support of IPM research and extension programs.

Table 4 presents the estimated ITSUR parameters of the demand functions of synthetic and nonsynthetic insecticides as well as syn-

Table 4. ITSUR Estimates of Per-Acre Pesticide Demand Equations, Peach Producers, 1995

Variable	Synthetic Insecticides		Nonsynthetic Insecticides		Synthetic Fungicides		Nonsynthetic Fungicides	
	Parameter Estimates	Standard Error	Parameter Estimates	Standard Error	Parameter Estimates	Standard Error	Parameter Estimates	Standard Error
INTERCEPT	2.246***	0.61	2.025***	0.59	3.436***	0.65	3.465***	1.03
p Price, crop[1]	0.009**	0.04	-0.004	0.004	0.006	0.004	0.001	0.006
w_1 Price, insecticide[2]	-0.007	0.05	0.004	0.05	-0.088*	0.05	-1.783**	0.08
w_2 Price, insecticide[2]	-0.186***	0.05	-0.086*	0.05	-0.101*	0.06	-0.324***	0.09
w_3 Price, fungicide[2]	-0.007	0.02	-0.012	0.02	0.016	0.02	-0.064**	0.03
w_4 Price, fungicide[2]	-0.013	0.02	0.009	0.02	-0.009	0.02	-0.014	0.04
R_1 Size[3]	-0.122	0.15	0.241 *	0.15	-0.209	0.17	0.150	0.26
R_2 Infestation level for insects[4]	0.178	0.21	-0.122	0.20	0.081	0.22	-0.207	0.35
R_3 Infestation level for diseases[4]	-0.018	0.20	0.308	0.20	-0.220	0.22	-0.680**	0.35
R_4 Predicted prob. biological[5]	-2.100***	0.64	-1.846***	0.62	-1.803***	0.69	-2.053*	1.10
R_5 Predicted prob. chemical[6]	2.912***	1.07	0.358	1.03	-0.126	1.15	3.633**	1.82
R_6 Predicted prob. cultural[7]	-0.051	0.73	0.733	0.70	-0.576	0.79	1.208	1.25
λ_{bio}[8]	-0.332	0.22	-0.425**	0.22	-0.452*	0.24	-0.491	0.38
λ_{CHEM}[8]	0.556**	0.25	0.632***	0.224	0.315	0.27	0.859**	0.42
λ_{CULT}[8]	-0.209*	0.12	-0.237**	0.12	-0.052	0.13	-0.305	0.21
Adjusted R-squared	0.17		0.07		0.11		0.18	

Dependent variables: Number of pesticide applications per year (x_1 synthetic insecticides, x_2 nonsynthetic insecticides, x_3 synthetic fungicides, and x_4 nonsynthetic fungicides).

[1] Actual price of fresh peaches, $/pound.

[2] Pesticide price in $/acre-per application ($w_1$ synthetic insecticides, w_2 nonsynthetic insecticides).

[3] Dummy variable equal to 1 for larger farms (> 150 acres), 0 otherwise.

[4] Infestation level dummy variable.

[5] Predicted value of probability of adoption of biological techniques.

[6] Predicted value of probability of adoption of chemical techniques.

[7] Predicted value of probability of adoption of cultural techniques.

[8] Inverse Mills ration, biological, chemical, and cultural techniques.

***, **, * significant at the 1-percent, 5-percent, and 10-percent level.

thetic and nonsynthetic fungicides. The overall goodness of fit as measured by the adjusted R-squared is reasonably good for all three equations, given the cross-sectional nature of the study. At least one coefficient of the inverse Mills ratios is significant in each of the equations, confirming that self-selection does occur.

Biological techniques significantly reduce insecticide use. Both the more toxic synthetic insecticides and the less toxic nonsynthetic insecticides are reduced in about the same percentage: the elasticity of demand of synthetic insecticides with respect to the probability of adoption of biological techniques is −0.32 (calculated at the mean) while that of nonsynthetic insecticides is −0.35. That is, a 10-percent increase in the probability of adoption of biological techniques would decrease the number of synthetic insecticide applications by 3.2 percent and decrease the number of nonsynthetic insecticide applications by 3.5 percent. Similarly, biological techniques reduce the more toxic synthetic fungicides (elasticity = −0.27) and the less toxic nonsynthetic fungicides (elasticity = −0.23). On the other hand, pesticide-efficiency techniques have an increasing effect on synthetic insecticide use (elasticity = 0.37) but the effect is insignificant for synthetic fungicides, while cultural techniques have an insignificant effect on both synthetic and nonsynthetic insecticides and fungicides. The increasing effect of pesticide-efficiency techniques on pesticide use may be due to scouting. Other studies have reported that by monitoring their fields farmers may detect potential pest damage sooner, use more pesticides, and obtain higher yields and returns than growers that spray according to calendar dates (Napit *et al.*). Other significant variables in the pesticide equations are pesticide price and crop price.

The regression results that biological techniques have a reducing effect on insecticide use may be illustrated by examining the average insecticide use at various levels of use of biological (and cultural) techniques. As the number of biological techniques used by peach farmers increases from 0 to 4, the number of applications (per year) of synthetic in-

secticides drops from 2.2 to 1.5, with a parallel decrease in the number of applications of non-synthetic insecticides (from 1.8 to 1.2 per year), and a corresponding drop in the number of applications of all insecticides (from 2.0 to 1.3). On the other hand, insecticide use changes little with the increase in the number of cultural practices and it has mixed behavior with respect to the number of chemical techniques.[5]

Concluding Comments

This paper presents a methodology with which to calculate the impact of adoption of bundles of major pest management techniques on pesticide use, broken down by major type and class. The method is applied to the case of peach producers in eight states accounting for most of the U.S. production. The method is applicable to the adoption of any technology. It accounts for self-selectivity and simultaneity, and the pesticide demand equations are theoretically consistent with a restricted profit function.

The empirical results show that different types of IPM techniques have different effects on pesticide use and toxicity. In the case of peach production, biological techniques tend to reduce pesticide use and pesticide toxicity substantially, while pesticide-efficiency techniques (using scouting and economic thresholds) have an increasing effect on pesticide use and toxicity, and cultural techniques do not have a significant effect on pesticide use and toxicity.

A limitation of the study is the weakness of some of the proxy variables used in the first stage (probit model), particularly the proxies for managerial ability (education, age, contracts). This limitation, important in the adoption of information intensive IPM, is attributed to data availability and may have caused the statistical insignificance of some of these variables in the model. We have also assumed that the peach growers are profit-maximizing producers operating in competitive markets,

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[5] This information has been graphed and is available on request from the authors.

and we have ignored the effect of production risk. These limitations will be surmounted when better data become available, helping improve our understanding of technology adoption in agriculture.

Moreover, these results are only valid for peach production and should not be extrapolated to other crops and regions. However, the methodology used has general validity. The paper also highlights an important factor in the analysis of the impact of IPM technologies: to gain a better understanding of the environmental impact of IPM it is helpful to first "unbundle" the IPM bundle.

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