The Microeconomic Impact of IPM Adoption: Theory and Application

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This paper develops a methodology to calculate the impact of integrated pest management (IPM) on pesticide use, yields, and farm profits. The methodology is applied to the IPM adoption among fresh market tomato producers in eight states. The method is of general applicability. It accounts for self-selectivity and simultaneity, and the pesticide demand and yield equations are theoretically consistent with a profit function. The results support the notion that fresh market tomato growers who adopt IPM for insects and diseases apply significantly less insecticides and fungicides, respectively, than do those who do not adopt IPM; IPM adoption has an insignificant effect on yields and a small effect on profits.

There is little doubt that pesticides are an important component of modern agriculture. Together with fertilizers and new hybrid seeds, pesticides have enabled American farmers to achieve unparalleled increases in land productivity over the last forty years.[1] Despite their positive effect, evidenced by the willingness of U.S. farmers to spend $7.2 billion on pesticides in 1994 (USDA 1996), the potential hazard of pesticides to human health and the environment have caused increased concern (Cooper and Loomis 1991; Hallberg 1987; Harper and Zilberman 1989; Mott 1991). The discovery of alar residues on Northwest applies, residues of banned pesticides (EBD and DBCP) and restricted-use pesticides (e.g., aldicarb) in Florida groundwater, and contamination of ground and surface water in several locations have heightened this already increasing public concern (Huang et al. 1994).

Recently, the U.S. Department of Agriculture (USDA), the Food and Drug Administration, and the Environmental Protection Agency have pledged to work together to reduce pesticide use in order to reduce the associated health and environmental risks. As integrated pest management (IPM) techniques were designed to address some of the health and environmental concerns of pesticides as well as the problem of pest resistance to pesticides, the USDA set a goal for the use of IPM on 75% of U.S. farmland by the year 2000. It is believed that 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, e.g., Kovach and Tette (1988) for New York apple producers; Greene et al. (1985) for Virginia soybean farmers; Harper et al. (1990) for Texas rice farmers; McNamara, Wetzstein, and Douce (1991) for Georgia peanut producers; Fernandez-Cornejo, Beach, and Huang (1994) for vegetable growers; and Wetzstein et al. (1985) for cotton producers. However, there are few published farm-level econometric studies on the effect of IPM on pesticide use, yields, and farm profitability.[2] Burrows (1983) studies the effect of IPM on pesticide use for a small sample of San Joaquin Valley cotton growers collected in 1970/74; Hall and Duncan (1984) consider the effect of IPM on profits for cotton growers using essentially the same data; Wetzstein et al. (1985) study the effect of IPM on yields, returns, and pesticide costs for a sample of cotton producers in Georgia; and Smith, Wetzstein, and Douce (1987) evaluate the effect of pest-management characteristics on net returns among a small sample of cotton, soybean, and peanut producers.[3]

Fruit and vegetable production is particularly intensive in pesticides. Expenditures on pesticides by fruit and vegetable growers (more than $100/

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[1] For example, corn production soared from 3 to 9.5 billion bushels over that period, while corn acreage decreased from 81 to 71 million acres (Fahnestock).

[2] See review by Norton and Mullen (1994).

[3] In related studies, Pingali and Carlson (1985) examine the effect of human capital on farmers' errors in assessing pest damage and pesticide use, using a sample of North Carolina orchards; and Hurd (1994) examines the effect of IPM on cotton yields and yield variability.

acre) were nearly seven times the agricultural average ($16 per acre) in 1990 (Fernandez-Cornejo, Beach, and Huang 1994); Gianessi and Puffer 1992). In addition, concerns about pesticide residues are especially important in fruits and vegetables, which are often consumed with little postharvest processing (National Academy of Sciences 1987). Tomatoes are the most important fresh market vegetable in terms of cash receipts. About 3.6 billion pounds, worth more than $1.1 billion, were produced on 130,000 acres in the United States in 1993 (USDA 1995). This vegetable is also important in terms of economic efficiency because ultimately the survival of winter vegetable farms in Florida and California (which together account for about 75% of the U.S. production of fresh market tomatoes) may depend on their ability to compete with Mexican growers (Fernandez-Cornejo 1994). The North American Free Trade Agreement (NAFTA) is intensifying this competition and bringing negative repercussions on less efficient farms.

The objective of this paper is to develop a methodology to calculate the impact of IPM on pesticide use, crop yields, and farm profits based on farm-level survey data and to apply the methodology to the case of adoption of IPM by fresh market tomato producers. Although Hall (1977) defines IPM as an attempt to reduce pesticide use while maintaining current production levels, the empirical evidence on the effects of IPM is mixed, even for a given crop. Burrows (1983) finds that IPM adoption leads to a significant reduction in pesticide expenditures for cotton growers in California, while Carlson (1980, p. 1002) cites evidence of "both complementary and substitute relationships between scouting and pesticide use" among cotton producers in North Carolina, and Wetzstein et al. (1985, p. 350) find that "IPM has no effect on pesticide expenditures" among a sample of Georgia cotton farmers. Theoretically, Taylor (1980) shows that IPM adoption may lead to an increase in pesticide use if acreage increases as a result of adoption. Wetzstein et al. (1985) demonstrate that IPM may increase pesticide use even if acreage is held constant. The effect of IPM on yields or farm profits is also mixed, but it appears to be more uniform. Greene and Cuperus (1991) and Norton and Mullen (1994) provide a summary of empirical results of the effects of IPM for vegetables and for crops in general.

What Is IPM?

IPM includes an assortment of techniques at the disposal of the producer, designed to maintain pest infestation at an economically acceptable level rather than attempting to completely eradicate all pests. While several of the techniques under the umbrella term IPM have been around for some time, and the unification of these practices into a cohesive group occurred about twenty-five years ago, the large-scale adoption of IPM techniques on U.S. farms is a fairly recent phenomenon. IPM gained prominence in the late 1960s and first received significant federal support in 1972.

There are several conceptual definitions of IPM. The Office of Technology Assessment (OTA 1979, 1:14) defined IPM as "the optimization of pest control in an economically and ecologically sound manner, accomplished by the coordinated use of multiple tactics to assure stable crop production and to maintain pest damage below the economic injury level while minimizing hazards to humans, plants, and the environment." The USDA has used the following definition: "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, Agricultural Research Service 1993).[4]

Location-specific growing conditions, such as temperature, humidity, and length of season influence pest populations and, consequently, the type and severity of pest problems. Just as pests are crop and location specific, IPM programs are specific to the crop and region for which they are designed (Vandeman et al. 1994). Moreover, the development of IPM programs has not been uniform across pest classes (insects, plant pathogens, weeds), crops, and regions.[5] Consequently, it is difficult to provide a general operational definition of IPM. Still, some general elements are common to most IPM programs. For example, both the OTA and the USDA definitions, as well as several others, have a common notion of using "natural" or "ecologically sound" techniques and the idea of preventing pests from reaching the "economic injury" or "economically damaging" level.

IPM is an information-intensive technology (Hall and Duncan 1984). Information is a funda-

[4] IPM does not exclude the use of synthetic pesticides. However, the pesticides used in IPM often differ from those used on a preventative or routine schedule. Where possible, IPM uses pesticides that target specific pests and are less toxic to beneficial organisms (Allen et al. 1987).

[5] In this paper, we use the term *insect* loosely to include insects proper and other arthropods, principally mites.

mental component of IPM, as pests and beneficial organisms need to be monitored. Scouting is the primary method of tracking pest populations by regular and systematic sampling of the fields to estimate pest infestation levels and subsequently determine if an economic threshold is reached (Vandeman et al. 1994). The second component of IPM is the use of economic thresholds. Treatment decisions are based on economically derived decision rules. These rules determine that a control strategy must be applied if and when an economic threshold is reached.

Economic thresholds are reached when the benefits of pest control begin to exceed the costs of control, so that net economic losses are avoided. Following Botrell, the economic threshold is the pest density (or amount of plant damage) at which the marginal cost of control just equals the marginal revenue of the crop. Economic thresholds are sometimes called action thresholds, control thresholds, or treatment thresholds (Botrell 1979). They are to be distinguished from the lower tolerance or damage threshold, at which point the pest damage is negligible, revenues are not lost, and the cost of control would not be justified economically (Carlson 1971). Determining the economic threshold for a particular pest may be complex, in particular for diseases (Apple 1977), as it must include "knowledge of pest biology and crop physiology as they relate to the environment, naturally occurring biological controls and the effects of possible control actions on other organisms in the environment" (Zalom et al. 1992, p. 7).

Most previous econometric studies have dealt with IPM adoption in general, without further specification of the type(s) of pest(s) 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 as: (1) IPM used to manage insects, (2) used to manage diseases, and (3) used to manage weeds. This concept has been used by Vandeman et al. (1994) and Taylor et al. (1993).

This paper considers IPM to manage insects and diseases. The adoption of IPM for insects and diseases is more prevalent among vegetable growers (Vandeman et al. 1994). In addition, Taylor et al. (1993) note that IPM techniques for controlling insects are the most developed of the three, and that insecticides and fungicides tend to be more toxic than herbicides. The following operational definition of IPM to manage insects (diseases) is used: A farmer is said to have adopted IPM to manage insects (diseases) (1) if the farmer reports having used both scouting for insects (diseases) and economic thresholds in making insecticide (fungicide) treatment decisions, and (2) the farmer reports the use of one or more additional insect (disease) management practices among those commonly considered to be IPM techniques.[6] The additional IPM techniques considered in this study include the use of pheromones (sex attractants often used in traps to monitor certain insects); alternating pesticides to slow the development of pest resistance to pesticides; adjusting planting dates to lessen pest problems; soil testing for pests; crop rotation; purchasing beneficial insects that prey on insects damaging to the crop; adjusting application rates, timing, and frequency of pesticide use to protect insects and other organisms that are beneficial to the crops; and the use of insecticides less harmful to beneficial insects.

Theoretical Framework

Three issues that have not been examined together by previous adoption studies need to be considered to develop the model. First, farmers' IPM adoption decisions and pesticide use may be simultaneous. This simultaneity may be due to unmeasured variables correlated with both IPM adoption and pesticide demand such as the size of the pest population, pest resistance, farm location, and grower perceptions about pest control methods (Burrows 1983). Second, farmers are not assigned randomly to the two groups (IPM adopters and nonadopters), but they make the adoption choices themselves. Therefore, 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 self-selectivity problem, unless corrected, could introduce serious bias in the results (Greene 1993; Berndt 1991). That self-selectivity occurs in actual practice for IPM adoption by cotton farmers was demonstrated by Hall and Duncan (1984). Roy (1951) was the first to discuss the self-selectivity problem. Heckman (1976, 1978, 1979), Amemiya (1998), and Lee (1982) discuss two-step estimation methods to correct for self-selectivity and simultaneity. Third, the

[6] The requirement of this operational definition of IPM to use an economically derived decision rule draws on Vandeman et al. (1994) and is similar to that used in the 1987 National Evaluation of Extension IPM programs (Napit et al. 1988).

demand for pesticidal inputs is a derived demand. Consequently, pesticide demand functions must be consistent with farmers' optimization behavior. For example, a demand function derived from a profit function should comply with some implicit symmetry restrictions in its parameters.

The adoption of a new technology is essentially a choice between two alternatives, the traditional technology and the new one. As such, choice models developed in consumer theory have been used to motivate adoption decision models (Fernandez-Cornejo, Beach, and Huang 1994). In this context, growers are assumed to make decisions by choosing the alternative that maximizes their perceived utility. Thus, grower i is likely to adopt IPM if the utility of adopting, U_{i1}, is larger than the utility of not adopting, U_{i0}. However, only the binary random variable I_i (taking the value of one if IPM is adopted and zero otherwise) is observed, as utility is unobservable (Maddala 1983). Moreover, because utilities are not known to the analyst with certainty, they are treated as random variables (Ben-Akiva and Lerman 1985; McFadden 1974). In the context of IPM adoption:

$$U_{ij} = V_{ij} + e_{ij},$$

where V_{ij} is the systematic component of U, related to the profitability of adopting ($j = 1$) and the profitability of not adopting ($j = 0$), and the random disturbance (e_{ij}) accounts for errors in perception and measurement, unobserved attributes and preferences, and instrumental variables (Ben Akiva and Lerman 1985, p. 55).

The probability that the ith grower will adopt IPM is

$$\begin{aligned} P_{i1} &= P\,(I_i = 1) = P\,(U_{i1} > U_{i0}) \\ &= P(V_{i1} - V_{i0} > e_{i0} - e_{i1}) \\ &= P(e_{i0} - e_{i1} < V_{i1} - V_{i0}). \end{aligned}$$

Assuming that the stochastic disturbances are independently and identically distributed normally, then their difference will also be normally distributed and $P_{i1} = P(I_i = 1) = F(V_{i1} - V_{i0})$, where $F(.)$ is the cumulative normal distribution. Taking a first-order Taylor series expansion of the functions V_{ij} in the parameters $\boldsymbol{\gamma}$, assuming that choice probabilities depend only on observed individual-specific characteristics (Judge et al. 1985) denoted by the vector $\mathbf{Z}$, and normalizing:

$$P_{i1} = P(I_i = 1) = F(\boldsymbol{\gamma}'\mathbf{Z}).$$

This transformation from $\mathbf{Z}$ to $P(0,1)$ is usually called the probit transformation, which is used to model the farmer's decision to adopt IPM. Thus, the probability of adoption equation is:

$$(1) \qquad P(I_k = 1) = F(\boldsymbol{\gamma}_k\, \mathbf{Z}_k)$$

where I_k denotes the adoption of IPM for insects ($k = 1$) and diseases ($k = 2$) and the explanatory variables (factors or attributes) for adoption included in $\mathbf{Z}$ are discussed in the next section.

To examine the impact of IPM on pesticide use, yields, and farm profits, one needs to estimate the pesticide demand functions and the supply function, as well as the variable profit function, as a simultaneous system. This paper accounts for simultaneity and self-selectivity by expanding Heckman's two-step procedure (1976) using a framework consistent with economic theory. First, the usual probit analysis is used to estimate the parameters $\boldsymbol{\gamma}_k$ of the adoption decision equation. The inverse Mills ratio $\lambda_k = \phi(\boldsymbol{\gamma}_k'\mathbf{Z}/\sigma_\mu)/\Phi(\boldsymbol{\gamma}_k'\mathbf{Z}/\sigma_\mu)$ 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; Lee 1982; Maddala 1983). Second, because I_k is endogenous, the predicted probabilities (obtained 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 well-developed restricted profit function (Gorman 1968; Diewert 1974; Lau 1976) is used to estimate theoretically consistent supply, demand, and profit equations. Consider n outputs, m variable inputs, s fixed inputs, and r other variables, such as locational or weather proxies. $\mathbf{Y} = (Y_1, \ldots Y_n)'$ denotes the vector of outputs: $\mathbf{X} = (X_1, \ldots X_m)'$ denotes the vector of variable inputs; $\mathbf{S} = (S_1, \ldots S_s)'$ is the vector of nonnegative quasi-fixed inputs; $\mathbf{R} = (R_1, \ldots R_r)'$ is the vector of other factors; $\mathbf{P} = (P_1, \ldots P_n)'$ denotes the price vector of outputs; and $\mathbf{W} = (W_1, \ldots W_m)'$ is the price vector of variable inputs. The restricted profit function is defined by:

$$(2) \qquad \pi(\mathbf{P},\mathbf{W},\mathbf{S},\mathbf{R}) = MAX_{\mathbf{Y},\mathbf{X}}[\mathbf{P}'\mathbf{Y} - \mathbf{W}'\mathbf{X}\colon \mathbf{Y},\mathbf{X} \in \mathrm{T}].$$

The production possibilities set T is assumed to be nonempty, closed, bounded, and convex. In addition, T is assumed to be a cone (Diewert 1974; Ball 1988). Under this 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:[7]

$$\pi(\mathbf{P},\mathbf{W},L,\mathbf{R}) = L \cdot \tilde{\pi}(\mathbf{P},\mathbf{W},\mathbf{R}) \tag{3}$$

where $\tilde{\mathbf{Y}} = \mathbf{Y}/L$, $\tilde{\mathbf{X}} = \mathbf{X}/L$ are the per acre output and input quantity vectors, and the per acre profit function is $\tilde{\pi} = \text{Max}_{\tilde{\mathbf{Y}}\tilde{\mathbf{X}}}\ (\mathbf{P}'\ \tilde{\mathbf{Y}} - \mathbf{W}'\ \tilde{\mathbf{X}}]$.

Using the Hotteling-Shephard lemma, the per acre supply and input demand functions are given by the following equations:

$$\tilde{\mathbf{Y}} = \frac{\partial\tilde{\pi}(\mathbf{P},\mathbf{W},\mathbf{R})}{\partial\mathbf{P}} \tag{4}$$

$$\tilde{\mathbf{X}} = \frac{\partial\tilde{\pi}(\mathbf{P},\mathbf{W},\mathbf{R})}{\partial\mathbf{W}}. \tag{5}$$

The Empirical Model

The IPM adoption equations estimated using the probit model are:

$$I_1 = \sum_j \gamma_{1j}\, z_{1j} + \mu_1 \tag{6}$$

$$I_2 = \sum_j \gamma_{2j}\, z_{2j} + \mu_2. \tag{7}$$

The components Z_j of the vector $\mathbf{Z}$ include the following factors or attributes of adoption: a risk proxy, farm size, expected output price, pesticide prices, farmer's education and experience, off-farm labor, use of consulting services, farm ownership, contractual arrangements for the production or marketing of the product, and regional proxies.[8] Because of data limitations, dummy variables are used as regional proxies for weather-related infestation conditions.[9] Both of the probit equations have the same regressors.

For the second stage, the empirical model uses a normalized quadratic variable profit function, which can be viewed as a second-order Taylor series approximation to the true profit function (Diewert and Ostensoe 1988). With symmetry imposed by sharing parameters and linear homogeneity imposed by normalization, this functional form may be expressed as:

$$\tilde{\pi}(\mathbf{P},\mathbf{W},\mathbf{R}) = a_0 + (\mathbf{a}'\mathbf{b}'\mathbf{c}') \begin{bmatrix} \mathbf{P} \\ \mathbf{W} \\ \mathbf{R} \end{bmatrix} + 1/2(\mathbf{P}'\mathbf{W}'\mathbf{R}') \begin{bmatrix} \mathbf{H} & \mathbf{G} & \mathbf{F} \\ \mathbf{G}' & \mathbf{B} & \mathbf{E} \\ \mathbf{F}' & \mathbf{E}' & \mathbf{C} \end{bmatrix} \begin{bmatrix} \mathbf{P} \\ \mathbf{W} \\ \mathbf{R} \end{bmatrix} \tag{8}$$

where $\mathbf{P}$ and $\mathbf{W}$ are vectors of normalized output and variable input prices, a_0 is a scalar parameter, while **a, b,** and **c** are vectors of constants of the same dimension as **P, W,** and **R.** The parameter matrices **B, C,** and **H** are symmetric and of the appropriate dimensions. Similarly **E, F,** and **G** are matrices of unknown parameters.

Using equations (4) and (8), the per acre supply function (in vector form) is:

$$\tilde{\mathbf{Y}}(\mathbf{P},\mathbf{W},\mathbf{R}) = \nabla_{\mathbf{P}}\tilde{\pi}(\mathbf{P},\mathbf{W},\mathbf{R}) = \mathbf{a} + \mathbf{HP} + \mathbf{GW} + \mathbf{FR}. \tag{9}$$

From equations (5) and (8), the per acre demand function for variable inputs is:

$$\tilde{\mathbf{X}}(\mathbf{P},\mathbf{W},\mathbf{R}) = \nabla_{\mathbf{W}}\tilde{\pi}(\mathbf{P},\mathbf{W},\mathbf{R}) = \mathbf{b} + \mathbf{G}'\mathbf{P} + \mathbf{BW} + \mathbf{ER}. \tag{10}$$

Considering the case of a single output, fresh market tomatoes, using the labor price as the numeraire, and appending the inverse Mills ratio terms as additional regressors to account for self-selection, as well as disturbance terms, the per acre supply function, per acre insecticide and fungicide

[7] PROOF:

$\pi(\mathbf{P},\mathbf{W},L,\mathbf{R}) = MAX_{\mathbf{Y},\mathbf{X}}[\mathbf{P}'\mathbf{Y} - \mathbf{W}'\mathbf{X}] = MAX_{\mathbf{Y},\mathbf{X}}[\mathbf{P}'L(\mathbf{Y}/L) - \mathbf{W}'L(\mathbf{X}/L)] = L \cdot MAX_{\tilde{\mathbf{Y}},\tilde{\mathbf{X}}}[\mathbf{P}'\tilde{\mathbf{Y}} - \mathbf{W}'\tilde{\mathbf{X}}]$.

[8] 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, delivery time, and price; it may also specify that the processor is to provide selected inputs. Marketing contracts, however, specify only price (or rules for setting the price) and other terms of the sale (Powers 1994).

[9] Ideally, pest infestation levels should be included (Reichelderfer 1980), but they were not available. Because of the data limitations, state dummy variables are used as proxies for pest infestation conditions.

demand functions, and per acre profit function become:

$$(11)\quad \tilde{Y} = a + HP + \sum_j G_jW_j + \sum_k F_kR_k + \theta_{y1}\lambda_1 + \theta_{y2}\lambda_2 + \epsilon_y$$

$$(12)\quad \tilde{X}_1 = b_1 + G_{11}P + \sum_j B_{1j}W_j + \sum_k E_{1k}R_k + \theta_{11}\lambda_1 + \theta_{12}\lambda_2 + \epsilon_1$$

$$(13)\quad \tilde{X}_2 = b_2 + G_{21}P + \sum_j B_{2j}W_j + \sum_k E_{2k}R_k + \theta_{21}\lambda_1 + \theta_{22}\lambda_2 + \epsilon_2$$

$$(14)\quad \tilde{\pi} = a_0 + aP + \sum_j b_jW_j + \sum_k c_kR_k + 0.5HP^2 + \sum_j G_{1i}PW_j + \sum_k F_{1k}PR_k + 0.5\sum_j\sum_i B_{ij}W_iW_j + \sum_k\sum_j E_{jk}W_jR_k + 0.5\sum_j C_{ik}R_iR_k + \theta_{31}\lambda_1 + \theta_{41}\lambda_2 + \epsilon_\pi$$

where now $\tilde{Y}$, P, a, H, and the ϵ's are scalars; and **F** and **G** are column matrices. The vector **R** includes two farm attributes (R_1 for contractual arrangements for production or marketing of the product and R_2 for farm size), the predicted probabilities of adoption of IPM for insects and diseases obtained from the probit model (R_3 and R_4), and three state dummies (R_5 for California, R_6 for Florida, and R_7 for North Carolina).

Data and Estimation

The data are obtained from the Agricultural Chemical Use Survey and its Economic Follow-On for Vegetables, administered between the fall of 1992 and the spring of 1993 by the National Agricultural Statistics Service of the U.S. Department of Agriculture (1993; hereafter referred to as the 1992 survey). The 1992 survey was conducted through on-site interviews based on a probability sample, drawn from a list frame based on all known commercial vegetable growers of the states selected. In order to be included in the list, the growers were required to have at least a tenth of an acre of production. A stratified sampling technique was used, where each stratum was a mutually exclusive set of the commodities of interest. The 1992 survey included fresh market tomato crops grown in eight states: California, Florida, Georgia, Michigan, New Jersey, New York, North Carolina, and Texas (table 1). Together these states account for 80% of the U.S. acreage planted for this crop (USDA 1995). After excluding observations with missing values, 199 usable observations of fresh market tomato growers are available for analysis.

The definitions of the variables used in this paper are detailed in table 2. Unlike Burrows (1983), who used expenditures (because of lack of data) in the pesticide demand equation, this paper uses the number of pesticide applications per year, which is a better measure of pesticide use.[10] Correspondingly, dollars per pesticide application per acre are used as pesticide price. Per acre variable profits are defined as per acre revenues (expected tomato prices times fresh market tomato yields) minus per acre variable costs (insecticides, fungicides, and associated labor costs).

With respect to IPM adoption, each farmer was asked to report separately the use of scouting for insects and diseases. Farmers were also asked what their decision criteria were for insecticide/fungicide application, i.e., whether they sprayed (1) on a preventative (routine) basis, (2) based on economic thresholds, or (3) using other criteria. In addition, each farmer was asked to report his/her use of other known techniques identified with IPM programs.

Unlike simple random sampling, the selection of an individual farm for the survey is not equally likely across all farms. Thus, weighted least squares estimation methods are used and the weights are equal to the inverse of the probability of selection.

The probit equations (6) and (7) are estimated separately.[11] Because the errors of the estimating equations for the second stage (equations [11]–[14]) are likely to be correlated, and 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 1962).

The impact of IPM adoption on pesticide use, yields, and farm profits is calculated from equations (11)–(14). For example, the effect of insect IPM on insecticide use is calculated from equation

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[10] Technically, the average number of 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.

[11] Seemingly unrelated regression (SUR) techniques are not necessary for the case in which regressors are the same across all the equations and there are no theoretical restrictions for the regression coefficients (Zellner 1962; Dwivedi and Srivastava 1978).

Table 1. Acres Planted and Pesticide Treated Area for Fresh Market Tomatoes in Survey States

State	Acres Planted	Percentage of Area Receiving Insecticides	Percentage of Area Receiving Fungicides	Percentage of Area Receiving Herbicides
California	37,000	96	72	61
Florida	49,400	100	100	96
Georgia	3,000	98	97	12
Michigan	2,700	72	81	65
New Jersey	5,000	85	72	48
New York	2,900	84	87	80
North Carolina	1,600	81	89	40
Texas	3,500	79	47	17
Total Surveyed States	105,100	95	86	75

SOURCE. USDA-NASS.

(12) since $\partial\bar{X}_1/\partial R_3 = E_{13}$. In elasticity form, the effect of an increase in the probability of adoption of insect IPM on insecticide use is $E_{13}(R_3/\bar{X}_1)$. Similarly, the effect of a change in the probability of adoption of insect IPM on variable farm profits per acre is calculated from equation (14): $(\partial\bar{\pi}/\partial R_3)(R_3/\bar{\pi})$. The elasticities reported are calculated at the means.

Results

Table 3 presents a summary of the data for fresh tomato farms. Separate results are given for adopters and nonadopters of IPM for insects and diseases. For a binary indicator variable, the mean represents the fraction of growers of each group with that attribute. For example, the variable SIZE shows that 62% of the adopters of IPM for insects operate large farms (more than 300 acres). In comparison, the continuous variables represent the actual means. For instance, the annual tomato yield obtained by adopters of IPM for insects is 28,900 pounds per acre, slightly higher than the yield for nonadopters. Table 3 also shows that, on average, adopters of insect IPM use 24% fewer insecticide applications than non adopters, although the differences are not significant. Moreover, while these

Table 2. Variable Definitions

Variable	Description
NAPPLI	Number of insecticide applications/year.
NAPPLF	Number of fungicide applications/year.
YIELD	Yield in thousand pounds/acre.
PFTOM	Actual price of fresh market tomatoes, $/pound.
PFTOME	Expected price of fresh market tomatoes, $/pound.
PAPPLI	Insecticide price in $/acre per application.
PAPPLF	Fungicide price in $/acre per application.
REVI	Revenues in thousand $/acre-year.
PROFIT	Variable profits in thousand $/acre-year.
CONTRAC	Dummy variable = 1 if farm sells its output under a production or marketing contract, 0 otherwise.
SIZE	Dummy variable = 1 for larger farms (>300 acres), 0 otherwise.
OCDAYS	Number of days/year worked off-farm for salary or wages.
OCYEARS	Operator experience: number of years operating a farm.
OWN	Fraction of acres owned with respect to total acres.
EDINT	Dummy variable for education (1 if completed high school or vocational training, 0 otherwise).
CHDEAL	Dummy variable = 1 if a chemical dealer is used for pest control information, 0 otherwise.
CONSUL	Dummy variable = 1 if a consultant is used for pest control information, 0 otherwise.
CALIF	Dummy variable = 1 if farm is located in California, 0 otherwise.
FLORI	Dummy variable = 1 if farm is located in Florida, 0 otherwise.
NCAROL	Dummy variable = 1 if farm is located in North Carolina, 0 otherwise.
PROBIPMI	Predicted value of probability of adoption of IPM for insects.
PROBIPMD	Predicted value of probability of adoption of IPM for diseases.
λ_{ins}	Inverse Mills ratio, IPM for insects.
λ_{dis}	Inverse Mills ratio, IPM for diseases

Table 3. Summary of Selected Variables—Fresh Market Tomato Producers

	IPM for Insects				IPM for Diseases			
	Adopters		Nonadopters		Adopters		Nonadopters	
Variable	Value	Std. error	Value	Std. error	Value	Std. error	Value	Std. error
NAPPLI	2.81	3.13	3.71	3.79	2.92	3.64	3.58	3.70
NAPPLF	6.07	7.78	6.73	6.78	6.00	6.59	7.52	7.01
YIELD	28.90	20.79	28.57	20.27	28.95	24.43	28.82	19.96
PFTOM	0.28	0.26	0.30	0.18	0.31	0.25	0.29	0.19
PFTOME	0.31	0.26	0.30	0.15	0.30	0.22	0.31	0.15
PAPPLI	10.18	3.99	9.33	2.10				
PAPPLF					6.88	6.42	6.13	4.75
REVI	7.59	7.99	8.88	9.46	7.72	7.89	8.70	9.44
SIZE	0.62	0.66	0.50	0.56	0.62	0.63	0.53	0.59
CONTRACT	0.13	0.45	0.06	0.26	0.12	0.41	0.06	0.26
CALIF	0.36	0.65	0.17	0.42	0.33	0.61	0.15	0.42
FLORI	0.53	0.67	0.63	0.54	0.54	0.64	0.68	0.55
NCAROL	0.01	0.14	0.02	0.16	0.02	0.17	0.02	0.18
PROFIT	7.06	8.20	8.48	9.58	7.41	7.57	8.15	9.71

averages may be helpful to determine the effect of IPM adoption (on pesticide use, yields, and farm profits) in a controlled setting (where farmers are randomly assigned to the two groups of adopters and nonadopters of IPM), with nonexperimental data other factors need to be controlled for in a regression framework.

The results from the probit regressions are given in table 4. Overall, both regressions are highly significant, as measured by likelihood ratio tests. Among the statistically significant coefficients, the expected price of the crop is positive, as anticipated, indicating that a higher expected price of the crop increases the probability of IPM adoption. The negative sign of the coefficient of the risk aversion proxy is also expected, supporting the notion that risk-averse farmers are less likely to adopt IPM (Fernandez-Cornejo, Beach, and Huang 1994). The coefficient of the consultant variable (which indicates whether a farmer used an independent consultant to obtain pest information) also carries the expected sign, positive, confirming that those farmers who rely on independent consultants are more likely to adopt IPM. Farmer experience is

Table 4. Results from Probit Regressions—Fresh Market Tomato Producers

	IPM for Insects		IPM for Diseases	
Variable	Parameter	Chi-square	Parameter	Chi-square
Intercept	−0.446	0.81	−0.570	1.12
Expected crop price (PFTOME)	1.569	5.98**	1.674	5.48**
Worked off-farm (OCDAYS)	−0.002	0.78	−0.005	3.28*
Experience of the operator (OCYEARS)	−0.019	4.17**	−0.009	0.70
Education (EDINT)	−0.075	0.08	−0.114	0.17
Fraction of the acres owned (OWN)	−0.085	0.31	−0.183	0.85
Farm size dummy (SIZE)	−0.113	0.16	−0.180	0.33
Risk-aversion proxy (MULTICROP)	−0.872	10.42***	−0.793	7.42***
Contract dummy variable (CONTRACT)	0.378	0.64	0.695	1.65
Chemical dealer used for pest control information (CDEALER)	0.074	0.06	−0.066	0.04
Consultant used for pest control (CONSUL)	1.40	18.52***	0.817	5.66***
Farm located in California (CALIF)	0.361	0.63	0.059	0.01
Farm located in Florida (FLORI)	−0.195	0.23	−0.407	0.85
Pearson chi-square/degrees of freedom	266.4***	177	231.6***	179
Likelihood ratio chi-square/degrees of freedom	276.1***	177	223.4***	179

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

negatively correlated with adoption, although in one case the coefficient is not significant. 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. The coefficient of the off-farm work hours variable is negative, as expected, confirming that the availability of operator labor has a positive influence on IPM adoption. This corroborates the findings by McNamara, Wetzstein, and Douce (1991) as well as those of Fernandez-Cornejo, Beach, and Huang (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.

Table 5 presents the estimated ITSUR parameters of the insecticide and fungicide demand functions and the per acre supply function for fresh tomato growers in the eight states. The overall goodness of fit ranges from fair for the insecticide demand and yield equations to very good (adjusted R-squared 0.32) for the fungicide equation, given the cross-sectional nature of the study. The two coefficients of the inverse Mills ratios (λ_1, λ_2) are significant in the insecticide demand equation, and λ_1 is significant in the per acre supply equation. These results suggest that self-selection does occur and it is significant. If left uncorrected, self-selection would have biased the estimates of the insecticide demand and yield equations.

Insecticide use is negatively related to the adoption of IPM for insects (significant at the 1% level). Similarly, fungicide use is negatively and very 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 -0.40 for the case of insecticides and -0.11 for fungicides (table 7). That is, a 10% increase in the probability of adoption of IPM for insects would decrease the number of insecticide applications by 4%, and a 10% increase in the probability of adoption of IPM for diseases would decrease the number of fungicide applications by 1%. By comparison, Pohronezny (1989) reports a 25% reduction in pesticide costs among IPM tomato users (relative to nonusers) in Florida, and Toscano et al. (1987) find a reduction in insecticide sprays among IPM fresh market tomato producers in California, ranging between 15 and 45%.

Table 5 shows that the impact of IPM on yields is insignificant. The effect of adoption of IPM for insects on yields is positive but not significant, while the effect of adoption of IPM for diseases on yields is negative but also not significant. These results are similar to those Toscano et al. (1987), who found no significant effect of adoption of insect IPM on yields of fresh market tomato in California, but different from those of Pohronezny (1989), who found that IPM increased yields of Florida tomatoes. Table 6 provides the ITSUR parameter estimates for profit function; about 50% of them are significant at the 1% level. The effect of IPM adoption on profits is positive but small: the elasticities of variable farm profits with respect to the probability of adoption of IPM is 0.01 for insects and 0.27 for diseases. This result means that an increase in the probability of adoption of IPM for insects would increase variable farm profits by

Table 5. ITSUR Regression Estimates for Per Acre Pesticide Demand and Supply Equations—Fresh Market Tomato Producers

	Insecticide Demand		Fungicide Demand		Per Acre Supply	
Variable	Parameter Estimate	t-value	Parameter Estimate	t-value	Parameter Estimate	t-value
INTERCEPT	4.658	4.30	0.983	1.08	17.602	2.21
PAPPLI	−0.569	−2.08	−0.060	−0.24	−3.024	−1.79
PAPPLF	−0.060	−0.24	−0.059	−0.32	1.828	0.98
PFTOME	−3.024	−1.79	1.828	0.98	−36.119	−1.69
CONTRACT	−0.081	−0.09	3.317	3.74	1.923	0.32
SIZE	−1.473	−4.11	0.344	1.08	1.799	0.63
CALIF	−0.243	−0.37	1.701	1.58	20.167	3.76
FLORI	1.079	1.43	9.165	11.21	17.526	3.18
NCAROL	2.406	3.09	−0.428	−1.06	−4.120	−0.79
PROBIPMI	−4.182	−5.47	−0.708	−1.09	6.073	0.82
PROBIPMD	4.501	4.10	−2.985	2.92	−12.302	−1.60
λ_{ins}	−0.632	−2.23	0.419	0.93	4.652	2.07
λ_{dis}	1.006	2.80	−0.823	−1.44	−2.809	−0.97
Adjusted R-squared	0.12		0.32		0.12	

Table 6. ITSUR Regression Estimates for Profit Function—Fresh Market Tomato Producers

Variable	Parameter Estimate	t-value
INTERCEPT	−11.23	−4.43
PAPPLI	4.658	4.30
PAPPLF	0.983	1.08
PFTOME	17.602	2.21
CONTRACT	−5.829	−2.17
SIZE	2.799	2.49
CALIF	−4.998	−1.67
FLORI	−10.247	−4.60
NCAROL	−4.222	−2.19
PROBIPMI	9.988	4.01
PROBIPMD	−0.378	−0.11
λ_{ins}	0.037	0.11
λ_{dis}	−0.579	−1.66
PFTOME*PFTOME	−36.119	−1.69
PFTOME*PAPPLI	−3.024	−1.79
PFTOME*PAPPLF	1.828	0.98
PAPPLI*PAPPLI	−0.569	−2.08
PAPPLI*PAPPLF	−0.060	−0.24
PAPPLF*PAPPLF	−0.059	−0.32
PFTOME*CONTRACT	1.922	0.32
PFTOME*SIZE	1.799	0.63
PFTOME*CALIF	20.167	3.76
PFTOME*FLORI	17.526	3.18
PFTOME*NCAROL	−4.121	−0.79
PFTOME*PROBIPMI	6.073	0.82
PFTOME*PROBIPMF	−12.302	−1.60
PAPPLI*CONTRACT	−0.081	−0.09
PAPPLI*SIZE	−1.473	−4.11
PAPPLI*CALIF	−0.242	−0.37
PAPPLI*FLORI	1.079	1.43
PAPPLI*NCAROL	2.406	3.09
PAPPLI*PROBIPMI	−4.182	−5.47
PAPPLI*PROBIPMF	4.501	4.10
PAPPLF*CONTRACT	3.317	3.74
PAPPLF*SIZE	0.344	1.08
PAPPLF*CALIF	1.701	1.58
PAPPLF*FLORI	9.165	11.21
PAPPLF*NCAROL	−0.428	−1.06
PAPPLF*PROBIPMI	−0.708	−1.09
PAPPLF*PROBIPMF	−2.985	−2.92

about 0.1%, while a 10% increase in the probability of adoption of IPM for diseases would increase variable profits by 2.7% (table 7).

Other results are derived from tables 5 and 6. Farm location, used as a proxy for weather-related pest infestation conditions, has a significant effect on pesticide demand and yields. Fresh market tomato farms located in Florida tend to use a significantly larger number of fungicide applications than do farms located in the rest of the country, while farms in North Carolina applied a significantly larger number of insecticide applications. These results are likely to be due to weather conditions. For example, the temperature and humidity in Florida facilitate the development of plant diseases. California farmers (followed by Florida farmers) tend to obtain significantly higher yields than do growers from the other states, but there is no discernible effect on profits.

Farms with production or marketing contracts tend to use a significantly larger number of fungicide applications, but production or marketing contracts do not affect significantly the number of insecticide applications. Yields are similar for farms under contract and the rest of the farms. Larger farms appear to use significantly larger amounts of insecticides, but size does not appear to have a significant impact on yields or fungicide use.

The own-price elasticities of the demand for insecticides and fungicides are both negative as expected. The estimated own-price elasticity of insecticide demand is −0.41, while the own-price elasticity of fungicide demand is −0.02. Cross-price elasticities of demand are small and insignificant.

Concluding Comments

This paper develops a methodology necessary to calculate the impact of integrated pest management (IPM) on pesticide use, yields, and farm profits. Next, the methodology is applied to the case of IPM adoption among fresh market tomato producers in eight states accounting for 80% of the U.S. production. The method is general enough to be applicable to the adoption of any technology. It accounts for self-selectivity and simultaneity by expanding Heckman's two-step method, and the pesticide demand and yield equations are theoretically consistent with a restricted profit function.

The results support the notion that, among fresh

Table 7. The Impact of IPM Adoption for Fresh Market Tomato Producers

	Elasticity with Respect to Probability of Adoption of IPM
Elasticity of pesticide use with respect to	
IPM for insects	−0.40
IPM for diseases	−0.11
Elasticity of yields with respect to	
IPM for insects	ns
IPM for diseases	ns
Elasticity of farm profits with respect to	
IPM for insects	0.01
IPM for diseases	0.27

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

market tomato growers, adopters of IPM for insects and IPM for diseases use significantly lower numbers of insecticide and fungicide applications than do nonadopters. The effect of IPM adoption on yields and profits is less clear. The adoption of IPM for insects and IPM for diseases does not have a significant effect on yields, and the effect of IPM adoption on variable profits is small. Other important determinants of pesticide demand, besides IPM adoption, are pesticide prices, farm location, contractual arrangements for the crop, and farm size.

Some limitations of the study are the incomplete modeling of the substitution possibilities between pesticides and other purchased inputs, particularly fertilizers. These limitations are not attributable to the methodology but are due to the lack of price input data for some inputs. As more data become available, these issues of substitutability may be addressed more thoroughly.

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