The Adoption of IPM Techniques By Vegetable Growers in Florida, Michigan and Texas

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Abstract

Factors influencing the adoption of Integrated Pest Management (IPM) techniques are studied using survey data from individual vegetable producers from Florida, Michigan, and Texas. Farmers who adopt IPM tend to be less risk averse and use more managerial time on farm activities than nonadopters. Adopters are also more likely to operate large, irrigated farms and use more family labor. Locational factors and the type of crop grown are also influential in IPM adoption. The analysis uses a logit framework and introduces adopter categories first conceptualized by rural sociologists.

Key Words: diffusion of innovations, integrated pest management, technology adoption, vegetables

Introduction

Synthetic pesticides were first actively marketed in the United States in the late 1940s, and their use has since played an integral role in the technological advances that have reduced agricultural labor requirements by half and doubled total factor productivity (USDA, ECIFS). Pesticide use, however, has also caused health and environmental concerns (Hallberg, Harper and Zilberman, Cooper and Loomis, Mott). Food safety considerations about pesticide residues are especially important in fruits and vegetables, because these commodities are often consumed with little post-harvest processing (National Academy of Sciences). In addition, fruit and vegetable production is particularly intensive in pesticidal inputs. In 1990, pesticide expenditures per acre by fruit and vegetable growers were nearly 7 times the agricultural average; U.S. farmers as a whole spent approximately $16 per acre for pesticides, while fruit and vegetable growers spent more than $100 per acre (USDA, Gianessi and Puffer).

Integrated Pest Management (IPM) techniques were designed to meet some of these health and environmental concerns and to address the problem of pest resistance to pesticides.[1] IPM combines biological, cultural, and chemical pest control techniques to reduce pest infestation to economically acceptable levels (Gianessi and Puffer). While IPM gained prominence in the late 1960s and first received significant Federal support in 1972, IPM adoption has moved quite slowly (Virginia Cooperative Extension Service).

There is a rich literature on the adoption of technological innovations in agriculture (Feder, Just,

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and Zilberman). Early research focused on the diffusion process: after a slow start in which only a few farmers adopt the innovation, adoption expands at an increasing time rate. Later, the rate of adoption decreases as the number of adopters begins to exceed the number of farmers who have not yet adopted. Finally, adoption asymptotically approaches its maximum level, until the process ends. This process results in an s-shaped diffusion curve, first discussed by rural sociologists and introduced to economics by Griliches in 1957.[2]

Economists and sociologists also want to understand what causes adoption rates to differ and what constrains the adoption of innovations. Several researchers have examined the influence of farmers' attributes on the adoption of agricultural innovations (e.g., Rahm and Huffman, Caswell and Zilberman). In the past, most adoption studies focused on technological innovations that increase productivity. Recent interest has shifted toward studies on the adoption of environmentally preferable technologies, such as IPM. The adoption of IPM techniques has recently been analyzed by Kovach and Tette for New York apple producers, J. K. Harper and others for Texas rice farmers, and McNamara and others for Georgia peanut growers.

The objective of this paper is to identify and quantify factors or attributes that influence IPM adoption decisions of individual vegetable producers in Florida, Michigan, and Texas. The identification and quantification of these factors will allow an increased understanding of the process of IPM adoption and will help provide policy guidance to promote adoption.

Most previous empirical studies have been limited to a local setting (county or clusters of counties) and have used mail or phone surveys. These surveys often have low response rates and are, consequently, subject to response bias.[3] The information used in this study was obtained through personal interviews conducted by trained and experienced enumerators. This study is also unique in that it considers three states, each with a different degree of IPM adoption.

Florida, Michigan, and Texas are among the most important vegetable-producing states. They cover a wide range of climates and produce a large variety of vegetables, including high-consumption items such as fresh tomatoes, onions, snap beans, sweet corn, cucumbers, and watermelons. Of the three states, Florida had the largest acreage in its vegetable farms, with 358,600 acres planted in 1990, followed by Texas, with 205,600 acres, and Michigan, with 159,200 acres (USDA, NASS). Pesticides were a very important input in vegetable production in all three states. In total, more than 80 percent of these acres were treated with insecticides in 1990, more than 75 percent were treated with herbicides, and more than 50 percent were treated with fungicides.

Sociological Views on the Adoption of Innovations

Rural sociologists conceptualize the innovation decision as a process comprised of several stages (Rogers). The farmer sequentially becomes aware, seeks information, and forms an opinion about the innovation. Next, the farmer decides whether or not to adopt. If the decision favors adoption, implementation follows. The process ends with confirmation of the decision or its eventual reversal. A major difference between this adoption process and other types of decision-making is the asymmetry in the uncertainty involved in deciding between the new and the known techniques. New techniques are usually adopted with incomplete information, whereas currently used techniques are better known and often applied with full information. The average time required for the adoption process varies across innovations and depends on the characteristics of the innovation, as perceived by the farmers.

Characteristics of Innovations and Their Rate of Adoption

According to Rogers, five characteristics of an innovation are essential to explain its rate of adoption: (1) the perception that the innovation is better than the traditional practice, due to economic or social factors, (2) its compatibility with tradition and past experience, (3) its complexity, (4) the feasibility that the innovation can be tried/experimented on a limited basis, and (5) the visibility of the results of the innovation.

The process of IPM adoption in the United States is now more than 20 years old. However, the process is far from complete. The slow rate of diffusion of IPM appears to be related to several of the characteristics listed above. First, given the stochastic nature of yields and production costs, quantifying the economic advantage of IPM is difficult for growers, at least in the short run. Second, unlike traditional chemical methods, which provide the farmer with precise recommendations, IPM is less precise and its recommendations are often in conflict with a farmers' intuition. For example, a recommendation to do nothing is inconsistent with the farmer's traditional notion of pest control. Also, IPM is often at odds with a grower's quality needs; for example, to control cosmetic damage (Kovach and Tette). Third, IPM is a complex, knowledge- and information-intensive technology (Hall and Duncan). Bultena reports that 49 percent of Iowa farmers acquainted with IPM thought that it was "complicated and difficult to use." Fourth, due to production externalities, experimenting with IPM on small portions of the farm may be difficult. Finally, results of using IPM are not clearly evident. It has been observed that farmers are naturally "skeptical when presented with an ill defined departure from a recognized practice that sounds more like ideology than usable procedure" (Office of Technology Assessment).[4]

Adopter Categories

Rural sociologists recognized early that essential differences among farmers can explain why all farmers do not adopt an innovation at the same time. Rogers used a time continuum to classify adopters into five categories based on their innovativeness, defined as the degree by which a farmer is relatively earlier in adopting, compared with other members in the system. Because many human attributes (physical or psychological) are normally distributed, Rogers hypothesized that the time to learn a given task is also normally distributed. Furthermore, he argued that substituting a social system for an individual, also leads to the normal distribution, which in the cumulative form approximates the typical s-shaped diffusion curve.[5] For that reason, Rogers used the standard normal distribution to define adopter categories.

Farmers in the first category are the "innovators." These individuals are characterized as venturesome and willing to assume the risk of using the innovation. They experiment and learn to adapt the innovation to local conditions. This category includes the first 2.5 percent of the adopters. The next 13.5 percent are the "early adopters." Farmers in this group play a key role in the diffusion process, because they are well respected by other farmers and exert a large degree of "opinion leadership." Next to adopt are the "early majority," which include 34 percent of the adopters. Farmers in this group deliberate for some time before adopting, waiting until sufficient experience has accumulated. Individuals in the "late majority" group (34 percent) are skeptics who are not convinced until most of their peers have adopted. The last group to adopt, the "laggards" (16 percent), are attached to tradition and suspicious of innovations and of "change agents." Laggards adopt only when they are certain that the innovation will not fail, because they can not afford failure due to their "precarious economic condition."

A drawback of this classification scheme for innovations that never reach 100-percent adoption is that it is not exhaustive because it excludes farmers that choose not to adopt. However, this problem is easily overcome by adding a long-run nonadopter category (which is assumed to account for 10 percent of the total population, as in Rogers) and renormalizing. The results are shown in Figure 1.

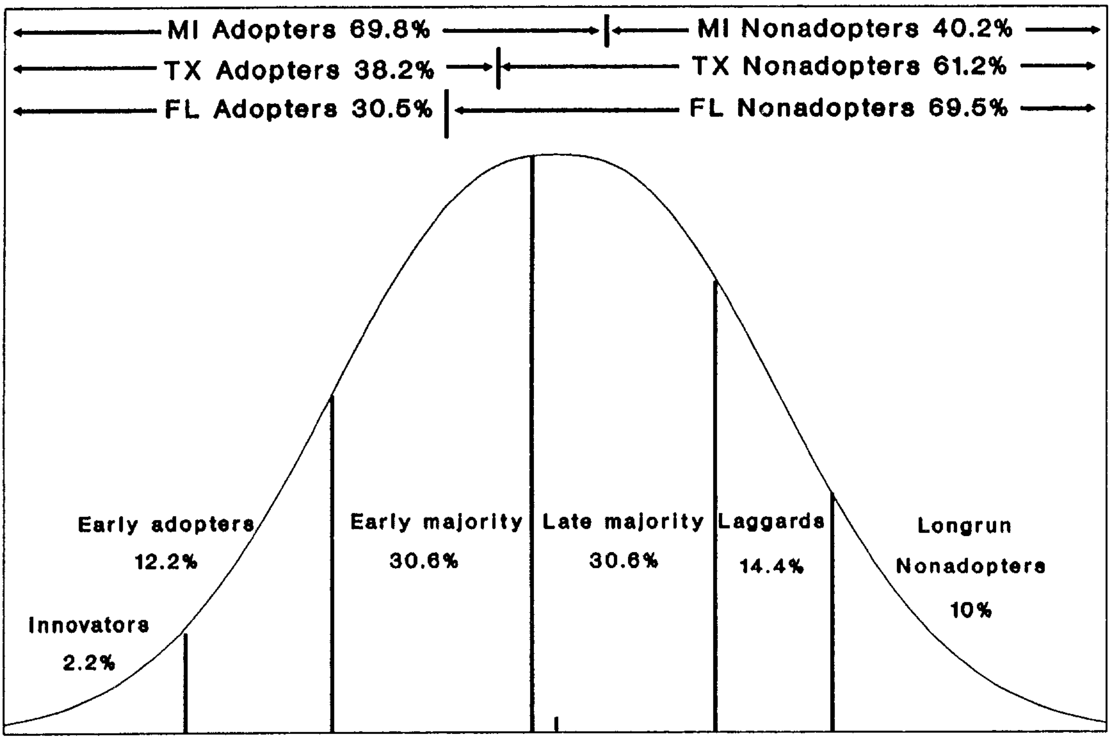
A New Consensus

The views described in this section form part of the adoption-diffusion perspective, which Ashby, Dunlap and Martin, and others criticized in the early 1980s. These critics accuse proponents of the adoption-diffusion perspective of having disciplinary blinders, neglecting crucial factors, such as the physical environment, in their analyses. More recently, a new consensus has emerged, integrating innovation-diffusion with physical, economic, and other factors (Nowak; Thomas et al.) This is the approach that we take in this study to formulate our hypotheses and analyze the results.

Hypotheses About the Factors Influencing Adoption

This section examines farmer attributes and locational factors that are hypothesized to be influential in the decision to adopt IPM. These hypotheses are later tested in a logit regression framework.

Figure 1. IPM adopter categories for Mi, TX, and FL vegetable growers



Risk Perceptions

In agriculture, the notion that innovations are perceived to be more risky than traditional practices has received considerable support in the literature. Many researchers argue that the perception of increased risk inhibits adoption (Feder, Just, and Zilberman). In general, when an innovation first appears, potential users are uncertain of its effectiveness and tend to view its use as experimental (Mansfield). Hiebert views adoption as a decision problem under uncertainty and develops a model to examine the effect of learning under uncertainty on the adoption decision. Feder and O'Mara further develop this idea using a Bayesian learning process to show that uncertainty declines with learning and experience, thus inducing more risk-averse farmers to adopt an innovation, provided it is profitable.

Risk is believed to be particularly critical in the adoption of a new technology for pest management because the effects of a subsequent crop loss are uncertain at the time a pest control strategy is used (Greene et al.). Bultena and Hoiberg empirically support this view, finding that adopters are less risk-averse than nonadopters. Kovach and Tette find that users of apple IPM indicate "a greater willingness to accept some risk in order to use all the scientific knowledge available to protect their crop." On the other hand, they report that a large percentage of non-users of IPM preferred to spray on an insurance or calendar basis.

In this study, the perception of risk is hypothesized to have a negative influence on IPM adoption. Innovators and early adopters of IPM are believed to be more inclined to take risks (they are relatively less risk averse) than are early- and late-majority farmers. Late adopters and laggards are likely to be the most risk averse.

To operationalize the concept of risk preferences using farmer attributes obtained from the survey, the study considers three factors generally associated with a farmer's risk attitudes. The first, debt-to-assets (DA) ratio, measures financial risk. Robison and Barry show that the optimal debt is inversely related to risk aversion, which is expected to be negatively related to adoption, leading to a positive relation between the DA ratio and adoption. However, Barry argues that farmers with a large DA ratio may also want to reduce their business risk, which would lead to the opposite sign for the correlation between the DA ratio and IPM adoption. This study appears to confirm that the first effect is larger.

Next, crop insurance is used as a proxy for a grower's revealed reluctance to assume risk. When growers purchase crop insurance, they transfer a portion of the yield risk to the insurance agency. Thus, the purchase of insurance reveals a risk-averse attitude and purchasers of insurance are less likely to adopt because of their aversion to risk.[6] Last, the total number of vegetable crops grown in a farm is used as a crude measure of output diversification, often associated with risk aversion (Freund).

Farm Structure

Another basic hypothesis is that the adoption of an innovation will tend to take place earlier on larger farms than on smaller farms. Just, Zilberman, and Rauser show that given the uncertainty, and the fixed transaction and information costs associated with innovations, there may be a critical lower limit on farm size, which prevents smaller farms from adopting. As these costs increase, the critical size also increases. It follows that innovations with large fixed transaction and/or information costs are less likely to be adopted by smaller farms. Nevertheless, Feder, Just, and Zilberman caution that farm size may be a surrogate for other factors, such as wealth and access to credit, scarce inputs, or information.

It is widely believed that landownership encourages adoption. Several empirical studies support this hypothesis. The views expressed in the literature are not unanimous, however, and the subject has been widely debated (Feder, Just, and Zilberman). For example, Bultena and Hoiberg find no support for the hypothesis that land tenure had a significant influence on the adoption of conservation tillage. In our view, the apparent inconsistencies in the empirical results are due to the nature of the innovation. Landownership is likely to influence adoption if the innovation requires investments tied to the land. Tenants are less likely to adopt these types of innovations because they perceive that the benefits of adoption will not necessarily accrue to them. Since IPM does not require land-tied investments, land tenure is not expected to affect IPM adoption.[7]

Operator labor measures the amount of time that the operator dedicates to farm activities and is inversely related to off-farm labor of the operator. As McNamara and others argue, IPM requires a substantial amount of the operator's time. Off-farm employment may present a constraint to IPM participation, because it competes for onfarm managerial time. Consequently, the availability of operator labor is hypothesized to have a positive influence on IPM adoption. Similarly, adoption of labor-intensive practices such as IPM is expected to be positively associated with the availability of family labor.

Crops Grown, Locational and Other Factors

Crop production variables are used to capture the effects of producing each major vegetable on IPM adoption. There are important differences on IPM adoption between the crops because of differences in the value of the crops, which influence profitability, as well as differences in the pests, in the availability of reliable IPM techniques, in the amount of managerial control and labor requirements, etc.[8] Crop variables are defined as indicator functions equal to one if a given crop is grown, zero otherwise. A positive (negative) and significant coefficient for a given vegetable crop indicates an increased (decreased) probability of IPM adoption if that crop is grown on a given farm. By comparison, livestock production is believed to limit IPM adoption, because livestock production is intensive in managerial and other labor.

Locational factors, such as soil fertility, rainfall, and temperature influence profitability differences among farms. The physical environment of the farm may affect profitability directly through increased fertility, and indirectly through its influence on pests. It is plausible that a farm located in a dry, infertile area is less likely to adopt IPM than a farm located in an adequately wet, fertile area. While weather (for example, monthly precipitation, temperature, and daylight hours), 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. In this study, dummy variables for regions within a state are used as locational proxies to account for the potential effect of environmental factors on adoption.

Irrigation may also influence adoption. Generally, irrigation increases yields and profitability, and reduces production risk. However, irrigation may also increase pest risk, because it encourages certain pest populations (Harper and Zilberman). Therefore, the net effects of irrigation cannot be predicted *a priori*.

Modeling Adoption Choices

A new technology will likely be adopted if its perceived utility is higher than the perceived utility of the old technology. Choice models developed in consumer theory have been used to motivate adoption decision models. In this context, vegetable growers are assumed to make their decisions by choosing the alternative that maximizes their perceived utility. Thus, the ith grower will adopt IPM if the utility of adopting, U_{i1}, is larger than the utility of not adopting, U_{i0}. Because there are errors in optimization and perception, the utility function is assumed to be random (McFadden). Thus, $U_{ij} = V_{ij} + e_{ij}$, $j = 1, 0$, where V_{ij} is a function of profits (which generally depend on a vector of choice characteristics, X_{ij}, and a vector of individual grower attributes and locational factors, Z_i), and the random disturbance (e_{ij}) accounts for unobserved variations in preferences and errors in perception and optimization. The probability of adoption is then $P_{i1} = P\ (\ U_{i1} > U_{i0}\ ) = P\ (\ V_{i1} - V_{i0} > e_{i0} - e_{i1}\ )$. Assuming that the stochastic components e_{i1} and e_{i0} are independently and identically distributed with a Weibull distribution, then their difference follows a logistic distribution (Maddala). Thus, the adoption decision may be analyzed using a logit model. Due to limitations in the data, it is often assumed that choice probabilities only depend on observed individual-specific characteristics (Judge et al.) In this case, taking a first-order Taylor series expansion of the functions V_{ij} in the parameters β, the log of relative odds of adopting IPM are: $\log (P_{i1}/P_{i0}\ ) = Z_i'\beta$, where the parameter vector β is alternative-specific. For continuous variables, the change in the probability of adoption relative to the change of the kth individual attribute is just the derivative of P_i with respect to Z_{ik}. In the discrete case, the change in probability attributable to the kth variable or attribute is equal to the difference in probability $P_i\ (\ Z_{ik} = 1) - P_i\ (\ Z_{ik} = 0)$ (Putler and Zilberman).

Data and Estimation

The Agricultural Chemical Use Survey and its Economic Follow-On for vegetables was administered by the National Agricultural Statistical Service between October 1990 and February 1991 in Arizona, Florida, Texas, and Michigan.[9] This survey employed a two frame probability sample: a list frame and an area frame. The list frame was based on all known commercial growers of fresh and/or processed vegetables, strawberries, or melons (hereafter called vegetables). These growers were required to have at least one-tenth of an acre of production to be included on the list. In comparison, the area frame was taken from the 1990 June Agricultural Survey Tracts, and was used only to provide additional information for the list frame.

A stratified sampling technique was used to draw the sample. Each stratum is a mutually exclusive set of the commodities of interest. Farms are partitioned such that each farm is associated with only one stratum. With respect to IPM, each interviewed farmer was asked to report the use of scouting for pest damage. In addition, farmers were asked about specific practices such as use of parasites (e.g., trichogamma), biochemical or microbial agents (B.t., pheromones, etc.), and cultural practices (rotation), which are usually considered to be IPM techniques. In this study the use of any of these practices classifies the farmer as a user of IPM techniques. After excluding variables with missing values, 190 usable observations remained for Florida, 178 for Texas, and 160 for Michigan.

Commonly used econometric estimation methods are inappropriate in this study, because the survey data were obtained from a stratified sample. Unlike simple random sampling, the selection of an individual farm for the survey is not equally likely across all farms on the list. Some farms have a higher probability of selection than others. Differences in the probability of selection introduce bias in simple maximum likelihood (ML) estimates of the parameters and their variances. In this study, logit models are estimated using a weighted least squares version of the ML method, where the weights are equal to the inverse of the probability of selection. Separate logit regressions are run for each state.[10]

The dependent variable is a binary variable equal to 1 if one or more IPM techniques is adopted and 0 otherwise. The following factors or attributes are included in the model as regressors:

1. Size: Dummy variable, equal to 1 if the farm is larger than 250 acres, 0 otherwise.

2. Operator labor: 1000 hours per year.

3. Family labor: Unpaid family labor, 1000 hours per year.

4. Debt ratio: Debt-to-total assets ratio.

5. Number of vegetables: Discrete variable equal to the total number of vegetables grown on each farm.

6. Crop insurance: Dummy variable, 1 if crop insurance is purchased, 0 otherwise.

7. Land tenure: Percent of land owned by the operator.

8. Irrigation: Percent of acres irrigated.

9. Livestock: Livestock revenues as a percent of total revenues.

10. Locational dummies: Two regions are considered for both Florida and Texas. In Texas, the east, with an annual precipitation of more than 50 inches, includes the 51 eastern counties (EASTD=1), and the west includes the remaining, dryer counties (less than 8 inches of precipitation). In Florida, the south includes the 10 southern counties (SOUTHD=1). While precipitation differences between the south and north are minor, temperature differences have caused Florida's fresh winter vegetable production to be located primarily in the south. Dummies are not used in Michigan, because large regional differences are not observed.

11. Crop variables: Binary indicator variables for each of the main crops grown in each State: tomatoes, melons, and sweet corn for Florida; melons, onions, and cabbage for Texas; asparagus, cucumbers, and snap beans for Michigan. The binary variable equals one if the given crop is grown on that farm.

To help analyze the logit regression results, Rogers' classification is used to characterize the types of farmers that comprise the adopter and nonadopter groups in each of the three States studied. The long-run nonadopters category is included in addition to the five groups proposed by Rogers. Accordingly, the bell-shaped curve is divided into six categories and renormalized to keep Rogers' relative proportions of the individuals per category (Fig. 1). An advantage of this modification is that the classification of adopter categories becomes mutually exclusive and exhaustive.

Results

Tables 1, 2, and 3 present the results from the statistical analysis of the vegetable survey data. Table 1 provides the mean values of the variables used in the logit analysis for both adopters and non-adopters. For a binary indicator variable, the mean represents the fraction of growers of each group with that attribute. For example, the farm-size variable for Texas shows that 60.9 percent of the adopters operated farms larger than 250 acres, while only 34.2 percent of the nonadopters operated larger farms. In comparison, the continuous variables represent the actual means. For instance, the mean debt-to-asset ratio for Michigan adopters is 0.235 and 0.205 for nonadopters. Table 1 also shows the degree of IPM adoption for each state. In Florida 30.5 percent of the farms have adopted IPM, compared with 38.8 percent in Texas, and 59.8 percent in Michigan.

Table 1. Means of Variables Used in Logit Analyses of Vegetable Farms in Three States

Variable	Florida adopters	Florida non-adopters	Texas adopters	Texas non-adopters	Michigan adopters	Michigan non-adopters
Size dummy	0.379	0.265	0.609	0.342	0.541	0.333
Operator labor, 1000 hours/year	2.517	1.834	2.760	1.920	2.514	1.610
Unpaid family labor, 1000 hours/year	0.744	0.427	0.953	0.575	1.944	0.663
Debt-to-assets ratio	0.325	0.126	0.200	0.099	0.235	0.205
Irrigation, fraction of the acres irrigated	0.566	0.295	0.367	0.342	0.214	0.037
Livestock production, fraction of total revenues	0.020	0.104	0.116	0.273	0.064	0.118
Land tenure, fraction of acres owned by operator	0.484	0.587	0.429	0.572	0.659	0.777
Crop insurance dummy	0.086	0.091	0.348	0.149	0.286	0.197
Number of vegetables	2.140	2.010	3.120	2.640	2.230	1.270
Melon production[a]	0.138	0.424	0.522	0.456		
Tomato production[a]	0.293	0.098				
Sweet corn production[a]	0.172	0.242				
Cabbage production[a]			0.203	0.061		
Onion production[a]			0.232	0.237		
Asparagus production[a]					0.122	0.379
Cucumber production[a]					0.276	0.152
Snap bean production[a]					0.214	0.047
SOUTHD/EASTD[b]	0.172	0.114	0.203	0.351		
Number of farms	58	132	69	109	98	66
Percent of farms adopting	30.5		38.8		59.8	

[a] Indicator variable defined in the text. [b] SOUTHD for Florida and EASTD for Texas

Tables 2 and 3 present the logit regression results for IPM adoption for vegetable growers in Florida, Texas, and Michigan. The overall goodness of fit is very good and the classification accuracy is about average (table 2) compared with other studies of IPM adoption. For example, using the transformed log likelihood function, which is distributed chi-squared, the null hypothesis that all regressors in the model are zero is strongly rejected at the one-percent level in each of the three states (p-values are about 0.0001). Similarly, the score statistic shows that the combined regressors are very significant (with a p-value of 0.001), and the McFadden R^2, which cannot be compared with a traditional R^2, is within the upper range of most other studies. Results are also good for the Akaike (information) and Schwartz criteria, which adjust the log likelihood function for the number of observations and the number of regressors in the model. These two criteria are often used to assess model fit and also model selection. Finally, the percent of concordant responses, used to determine the predictive ability of the model, varies from 80 percent for Texas to 84 percent for Michigan, and the percent of correct responses is about 70 percent, within the range of other studies.

About 90 percent of the coefficients are statistically significant (table 3). Among the factors related to risk, the coefficient of debt-to-assets ratio

Table 2. Logit Regression Results - Overall Measure of Fit

Dependent variable	Florida	Texas	Michigan
Number of observations	190	178	166
-2 log likelihood function for covariates	359***	313***	945***
p-value (for likelihood function)	0.0001	0.0001	0.0001
McFadden R^2	0.305	0.229	0.440
Score statistic	318	284	736
Concordant, percent[a]	81.3	79.8	84.2
Correct, percent	71.4	68.5	71.9
Sensitivity, percent[b]	51.7	53.6	79.6
Specificity, percent[c]	80.6	78.0	59.7

[a] Percent of pairs of observations with different responses in which the larger response has a higher probability than the smaller response.
[b] Percent of IPM adopters predicted as such
[c] Percent of nonadopters predicted as such
(*) Significant at the 10-percent level
(**) Significant at the 5-percent level
(***) Significant at the 1-percent level

in Florida and Texas is positive and significant at the one-percent level. This positive relationship between the DA ratio and adoption indicates that the negative effect of risk aversion on adoption is larger than the "Barry effect" (farmers with a high DA ratio may be seeking to reduce their business risk). However, the DA ratio in Michigan is significant and of the opposite sign. This may be due to a stronger Barry effect for Michigan farmers. Alternatively, the negative sign may be explained by the advanced degree of IPM adoption in Michigan compared with the other two states. As the degree of adoption increases, later adopters who have different attributes than innovators and early adopters are included in the adopters group. Adopters in Florida and Texas include all innovators, early adopters, and a fraction of the early majority (fig. 1). On the other hand, the adopters in Michigan include all innovators, early adopters, early majority, and a large fraction of late majority adopters (fig. 1). As a result, many of the differences in farmer attributes between adopters and nonadopters in Michigan become blurred, reducing the reliability of the individual coefficients in the regression.

The crop insurance variable does not appear to be related to adoption. The coefficient is negative, as expected under the hypothesis that risk aversion hinders adoption, but insignificant for Florida and Michigan. The coefficient is positive and insignificant in Texas. The third variable used to capture a grower's risk preference is the number of vegetable crops grown. The coefficient is positive in all three states, as expected if risk aversion is to be negatively related to adoption, although it is insignificant in Florida. The result for Florida may be due to the fact that this variable is influenced by other factors in addition to risk diversification; for example, for many farms this variable may be measuring the effect of multiple cropping, where several crops may be grown sequentially on the same field during the same year. In any case, considering the overall effect of the three proxies of risk aversion, the hypothesis that risk preferences have no influence on a grower's

Table 3 Logit Regression Results of IPM Adoption by Vegetable Growers in Three States[a]

Dependent	Florida		Texas		Michigan	
Dependent variable IPM	Parameter estimates	Change in probability[b]	Parameter estimates	Change in probability[b]	Parameter estimate	Change in probability[b]
Intercept	-2.21 (0.27)		-2.78 (0.26)		-1.59 (0.21)	
Size	0.40* (0.23)	0.068	0.72*** (0.19)	0.212	0.10 (0.18)	0.009
Operator labor	0.31*** (0.10)	0.050	0.57*** (0.09)	0.097	0.79*** (0.10)	0.371
Unpaid family labor	0.43*** (0.10)	0.071	0.10* (0.06)	0.018	0.35*** (0.07)	0.098
Debt-to-assets ratio	1.04*** (0.34)	0.170	0.99*** (0.36)	0.168	-0.87*** (0.30)	-0.048
Irrigation	1.46*** (0.28)	0.239	1.28*** (0.27)	0.218	2.64*** (0.56)	0.063
Livestock production	-1.93** (0.78)	-0.316	-1.30*** (0.32)	-0.221	-2.57*** (0.34)	-0.056
Crop insurance	-0.35 (0.35)	-0.052	-0.12 (0.20)	0.020	-0.08 (0.20)	-0.004
Number of vegetables	0.05 (0.08)	0.008	0.11*** (0.04)	0.019	0.20*** (0.07)	0.082
Melon production	-1.94*** (0.22)	-0.287	0.08 (0.19)	0.013		
Tomato production	1.17*** (0.28)	0.261				
Sweet corn production	-0.11 (0.28)	0.019				
Cabbage production			1.39*** (0.35)	0.302		
Onion production			-1.65*** (0.26)	-0.202		
Asparagus production					-1.98*** (0.20)	-0.202
Cucumber production					0.61** (0.24)	0.023
Snap bean production					2.28*** (0.35)	0.069
SOUTHD/EASTD[c]	-0.78*** (0.28)	-0.015	0.32 (0.21)	0.058		

[a] Standard errors in parentheses [b] Calculated at the means [c] EASTD for Texas and SOUTHD for Florida
(*) Significant at the 10-percent level (**) Significant at the 5-percent level (***) Significant at the 1-percent level

decision to adopt IPM is rejected at the 1 percent level for Texas and Michigan and at the 5 percent level for Florida.

For the variety of reasons mentioned earlier, large farms are more likely to adopt IPM than are smaller farms. In all three states, farm size is positively correlated with adoption. The coefficient is significant in Florida and Texas. The positive, yet insignificant, effect of farm size on adoption in Michigan is not surprising, given the relatively advanced degree of adoption in that state.

Operator labor, which also reflects off-farm activities by some operators, is positive and significant at the one-percent level in all three states. This suggests that managerial time has a significant influence on a grower's decision to adopt IPM. Unpaid family labor is also significant and positive in all three states. The availability of unpaid family labor increases the probability of adoption. Irrigation is positive and significant at the one-percent level in all three states. This suggests that the increased yield and profitability characteristics outweigh any increase in pest risk, which may be associated with irrigation in the IPM adoption decision. Only the regressions for Florida and Texas include location variables. In Texas, we find a positive but insignificant (p-value of 0.13) relationship between precipitation (prevalent in east Texas) and IPM adoption. In contrast, in Florida the relationship is negative and significant, suggesting that southern Florida growers were less likely to adopt IPM. The reason for this sign is unclear, although the increased incidence of pests in South Florida may partially account for it.

The differences in IPM adoption among the major vegetables grown is captured by the crop production variables (table 3). The production of five of the major vegetables increases the probability of IPM adoption. For example, in Florida, the probability of adopting IPM for a grower producing tomatoes is 26.1 percent higher than that of a farmer not growing tomatoes. On the other hand, the probability of adoption is 28.7 percent lower for a Florida grower producing melons compared to a Florida grower not producing melons. With respect to the livestock production variable, a negative and significant effect of livestock production on IPM adoption is found in all three states. This supports our hypothesis that raising livestock limits the amount of time the operator can devote to IPM.

The land tenure variable was dropped from the final model because, as hypothesized, the variable was statistically insignificant in all three states. While it is sometimes believed that adoption is positively correlated with landownership, as mentioned earlier, IPM does not require costly fixed capital, such as buildings, land-improvements, or other investments tied to the land that a tenant would probably forgo. Rather, the IPM investment is in human capital and not tied to rented land.

Conclusions

Given the distributional consequences of adoption, which became apparent in many countries after the Green Revolution, examining the influence of farm structure on technology adoption is particularly interesting. A unique feature of this study is the different degrees of adoption across three states, ranging from 31 percent in Florida to 60 percent in Michigan. By incorporating into our analysis some perspectives of rural sociologists, especially the classification of adopters, we improve our interpretation of the empirical results. In particular, the more advanced degree of IPM adoption in Michigan compared with the other two states explains the decreased reliability of several of the coefficients in the logit regression for Michigan.

Our results generally support the notion that early adopters are more inclined to risk-taking than are nonadopters. Farm size is a significant factor in Florida and Texas, confirming our expectation that large farms are more likely to adopt IPM than smaller farms. Furthermore, the positive, yet insignificant effect of farm size on adoption in Michigan is explainable. The degree of IPM adoption is more advanced in Michigan, blurring the differences in farmer attributes between adopters and nonadopters, and consequently reducing the reliability of individual coefficients in the regression. Operator and unpaid family labor are significant and positive in all three states, showing that both the quantity and quality (managerial and non-managerial) of labor affect the adoption decision. Moreover, the significant and negative effect of the livestock production variable reinforces our hypothesis that managerial time is essential in the adoption of IPM.

IPM and irrigation are found to be complementary technologies, perhaps because the increased profitability that irrigation affords to farms, also makes IPM profitable. Crop and locational variables are also influential in the IPM adoption decision. Farm ownership is not a factor in IPM adoption because IPM does not require investments tied to the land.

The data limits this study, particularly in relation to the amount of information on farmer attributes, such as education, age, use of extension services, etc. Also, the lack of information about the timing of various IPM practices in relationship to different pest populations prevents a sequential analysis of the decision process.

References

Ashby, J. A. "The Social Ecology of Soil Erosion in a Colombian Farming System." *Rur. Soc.* 50(1985): 377-96.

Bultena, G. L. "Sociological Factors in Conservation Adoptions: A Study of Reduced Tillage and IPM." Integration of Pest Management and Conservation Tillage. Proceedings of North Central Region Workshop, St. Louis, MO, 1985.

Bultena, G. L., and E. O. Hoiberg. "Factors Affecting Farmers' Adoption of Conservation Tillage." *J. Soil and Water Conserv.* May-June(1983):281-84.

Burrows, T. M. "Pesticide Demand and Integrated Pest Management: A Limited Dependent Variable Analysis." *Am. J. Agr. Econ.* 65(1983):806-10.

Caswell, M., and D. Zilberman. "The Choices of Irrigation Technologies in California." *Am. J. Agr. Econ.* 67(1985):224-34.

Cooper, J., and J. Loomis. "Economic Value of Wildlife Resources in the San Joaquin Valley: Hunting and Viewing Values." In *The Economics and Management of Water and Drainage in Agriculture*, edited by A. Dinar and D. Zilberman. Norwell, MA: Kluwer Acad. Press, 1991.

Council on Environmental Quality. "Report to the President: Progress Made by Federal Agencies in the Advancement of Integrated Pest Management." Washington, D.C., 1980.

Dunlap, R. E., and K. E. Martin. "Bringing Environment into the Study of Agriculture: Observations and Suggestions Regarding the Sociology of Agriculture." *Rur. Soc.* 48(1983):201-18.

Feder, G., and G. O'Mara. "Farm Size and the Diffusion of Green Revolution Technology." *Econ. Develop. and Cultur. Change.* 30(1981):59-76.

________________________. "On Information and Innovation Diffusion: A Bayesian Approach." *Am. J. Agr. Econ.* 64(1982):145-47.

Feder, G., R. J. Just, and D. Zilberman. "Adoption of Agricultural Innovations in Developing Countries: A Survey." *Econ. Develop. and Cultur. Change.* (1985):255-98.

Fomby, T. B., R. C. Hill, and S. R. Johnson. *Advanced Econometric Methods.* New York: Springer-Verlag, 1984.

Freund, R. J. "The Introduction of Risk into a Programming Model." *Econometrica.* 21(1954):253-63.

Greene, C. R., R. A. Kramer, G. W. Norton, E. C. Rajotte, and R. M. McPherson. "An Economic Analysis of Soybean Integrated Pest Management." *Am. J. Agr. Econ.* 67(1985):567-72.

Gianessi, L. P., and C. A. Puffer. "Reregistration of Minor Pesticides: Some Observations and Implications." *Inputs Situation and Outlook Report.* U.S. Dept. of Agr., Economic Research Service, February (1992):52-60.

Griliches, Z. "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica.* 25(1957):501-22.

Hall, C. H., and G. Duncan. "Econometric Evaluation of New Technology with an Application to Integrated Pest Management." *Am. J. Agr. Econ.* 66(1984):624-33.

Hallberg, G. R. "Agricultural Chemicals in Ground Water: Extent and Implications." *Am. J. Alternative Agr.* 2(1987):3-15.

Harper, C. R., and D. Zilberman. "Pest Externalities from Agricultural Inputs." *Am. J. Agr. Econ.* 71(1989):692-702.

Harper, J. K., M. E. Rister, J. W. Mjelde, B. M. Drees, and M. O. Way. "Factors Influencing the Adoption of Insect Management Technology." *Am. J. Agr. Econ.* 72(1990):996-1005.

Hiebert, L. D. "Risk, Learning, and the Adoption of Fertilizer Responsive Seed Varieties." *Am. J. Agr. Econ.* 56(1974):764-68.

Judge, G. C., W. E. Griffiths, R. C. Hill, H. Lutkepohl, and Tsoung-Chao Lee. *The Theory and Practice of Econometrics*, second edition. New York: John Wiley & Sons, 1985.

Just, R. E., D. Zilberman, and G. C. Rauser. "A Putty-Clay Approach to the Distributional Effects of New Technology Under Risk." In *Operations Research in Agriculture and Water Resources*, edited by D. Yaron and C. Tapiero. New York: North Holland Publishing Company, 1980.

Kovach, J. and J. P. Tette. "A Survey of the Use of IPM by New York Apple Producers." *Agricultural Ecosystems and Environment.* 20(1988):101-8.

Maddala, G. S. *Limited-Dependent and Qualitative Variables in Econometrics.* Cambridge University Press, 1983.

Mansfield, C. K. *Industrial Research and Technological Innovation.* New York: Norton, 1966.

McFadden, D. "Conditional Logit Analysis of Qualitative Choice Behavior." In *Frontiers in Econometrics*, ed. P. Zaremka. New York: Academic Press, 1974.

McNamara, K. T., M. E. Wetzstein, and G. K. Douce. "Factors Affecting Peanut Producer Adoption of Integrated Pest Management." *Rev. Agr. Econ.* 13(1991):129-39.

Mott, L. "The Public Residue Database." In *Pesticide Residues and Food Safety: A Harvest of Viewpoints*, ed. B. G. Tweedy, H. J. Dishburger, L. G. Balantine, and J. McCarthy. Washington, DC: American Chemical Society, 1991.

National Academy of Sciences. *Regulating Pesticides in Food.* Washington, D.C.: National Academy Press. 1987.

Nowak, P. J. "The Adoption of Agricultural Conservation Technologies: Economic and Diffusion Explanations." *Rur. Soc.* 52(1987):208-20.

Putler, D. S., and D. Zilberman. "Computer Use in Agriculture: Evidence from Tulare County, California." *Am. J. Agr. Econ.* 70(1988):790-802.

Office of Technology Assessment. *Pest Management Strategies: Volume II - Working Papers.* Washington, D.C., 1979.

Rahm, M. R., and E. Huffman. "Adoption of Reduced Tillage: The Role of Human Capital and Other Variables." *Am. J. Agr. Econ.* 66(1984):405-13.

Robison, L. J., and P. J. Barry. *The Competitive Firm's Response to Risk.* New York: Macmillan Publishing Company, 1987.

Rogers, E. M. *Diffusion of Innovations,* third edition. New York: Free Press, 1983.

Slavin, R. E. *Educational Psychology: Theory into Practice,* second edition. Englewood Cliffs, NJ: Prentice Hall, 1988.

Thomas, J. K., H. Ladewig and W. A. McIntosh. "The Adoption of Integrated Pest Management Practice Among Texas Cotton Growers." *Rur. Soc.* 55(1990):395-410.

U.S. Dept. of Agr., Economic Research Service. *Agricultural Resources: Inputs, Situation and Outlook Report.* Selected years.

U.S. Dept. of Agr., Economic Research Service. *Economic Indicators of the Farm Sector: Production and Efficiency Statistics, 1990,* ECIFS 10-3, May 1992.

U.S. Dept. of Agr., National Agricultural Statistics Service (NASS). "*Agricultural Chemical Use: 1990 Vegetables Summary.*" June 1991.

Virginia Cooperative Extension Service (VCES). "The National Evaluation of Extension's Integrated Pest Management Programs." In association with Virginia Technical University and the U.S. Department of Agriculture, Blacksburg, VA. 1987.

Willey, W. R. Z. "Barriers to the Diffusion of IPM in Commercial Agriculture." In *Pest Control Strategies,* ed. E. Smith and D. Pimentel. New York: Academic Press, 1978:285-307.

Endnotes

1. The Office of Technology Assessment (OTA) defines 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." IPM is likely to play a lead role in the transition from a chemical-intensive to a low-input sustainable agriculture.

2. S-shaped diffusion was first observed by the French sociologist Tarde in 1903. As Rogers notes, Tarde also offered his "laws of imitation," including the view that adoption is more likely for innovations that have some similarity to ideas already accepted.

3. The average response rate from six recent adoption studies in agriculture was approximately 60 percent, with a range of 17 to 89 percent.

4. In addition, Gianessi and Puffer argue that pesticide registration has disrupted several successful IPM programs used in the production of vegetables. Because of the expense and time necessary to reregister pesticides, chemical manufacturers have dropped many of their low volume products, including many selective pesticides necessary for IPM programs.

5. A social system is a group of interrelated units (individuals or organizations) seeking to solve a common problem in order to reach a collective goal (Rogers).

6. Moral hazard, in the sense that insurance purchasers would be more inclined to adopt IPM because they feel protected by crop insurance, is unlikely to occur because a grower that purchases crop insurance can only be protected up to 75 percent of previous (average) yields.

7. It is also plausible that landowners may have some influence on the adoption decisions of their tenants, as pointed out by a referee. This situation may occur in some special cases (e.g., for share croppers) and poses additional hurdles to adoption. We have no evidence to support this possibility among vegetable farmers. In addition, the statistical tests show the ownership variable to be insignificant.

8. Griliches showed in 1957 that, in the longer run, differences in the rate of adoption of hybrid corn can be explained by differences in profitability.

9. Arizona was excluded from our study due to the small number of usable observations.

10. Tests in preliminary runs showed that pooling all the data together and using intercept shifters was not adequate. Large interstate differences in production structure, degree of adoption, weather, and soils affect both the intercept and the slopes of the logit regression.