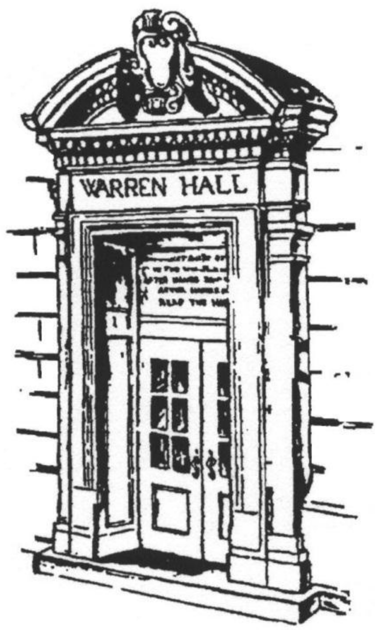
WP 2011-19
November 29, 2011



Working Paper

Dyson School of Applied Economics and Management
Cornell University, Ithaca, New York 14853-7801 USA

Factors Influencing Adoption of Integrated Pest Management in Northeast Greenhouse and Nursery Production

Jie Li, Miguel I. Gómez, Bradley J. Rickard and Margaret Skinner

Factors Influencing Adoption of Integrated Pest Management in Northeast Greenhouse and Nursery Production

Jie Li
Research Assistant
Charles H. Dyson School of Applied Economics and Management
Cornell University
Ithaca, NY 14853
607-280-8926
jl2522@cornell.edu

Miguel I. Gómez
Assistant Professor
Charles H. Dyson School of Applied Economics and Management
Cornell University
321 Warren Hall
Ithaca, NY 14853
607-255-8159
mig7@cornell.edu

Bradley J. Rickard
Assistant Professor
Charles H. Dyson School of Applied Economics and Management
Cornell University
339 Warren Hall
Ithaca, NY 14853
607-255-7417
bjr83@cornell.edu

Margaret Skinner
Research Professor
University of Vermont Entomology Research Laboratory
661 Spear Street,
Burlington, VT 05405-0105
802-656-5440
mskinner@uvm.edu

November 2011

The authors thank Elizabeth M. Lamb, Ornamental IPM Coordinator of the New York State Integrated Pest Management Program, for providing advice on approaches to the measurement of IPM adoption in Ornamental Crops. The authors also thank Professor Nelson Bills for comments on earlier drafts of the manuscript. This work was supported in part by grants from the USDA: Hatch (VT-HO1408, Regional Project S-1024) and the Specialty Crops Research Initiative (Project # 2008-51180-04886).

Factors Influencing Adoption of Integrated Pest Management in Northeast Greenhouse and Nursery Production

Abstract

We surveyed 94 greenhouse and nursery growers in three Northeastern states to examine factors that influence integrated pest management adoption. We constructed four alternative dependent variables describing the extent of IPM adoption, and employ Logit, Ordered Logit and Tobit models to identify factors affecting IPM adoption. We find that IPM adoption is more likely to occur on large farms that hire more full-time workers, and have more diversified crops. Greenhouse and nursery operations that face disease problems are less likely to adopt IPM, and availability of biological control agents limits IPM adoption. Our analysis also highlights differences between the self-reported and more objective IPM measures.

Keywords: Greenhouse and Nursery Production, Integrated Pest Management, Northeast United States, Technology Adoption

JEL Codes: O33, Q13, Q16

Introduction

The income-generating potential of greenhouse and nursery products far exceeds that of most traditional crops in New England and the greater Northeast region. The 2009 Census of Horticulture Specialties counts 1,472 operations in the six New England states of the Northeast, a decrease of 218 operations since the 1998 Census of Horticulture Specialties. The total retail value of horticultural crops exceeded $431 million, an increase of 53.1 percent over this period (Census of Horticulture Specialties 1998 and 2009). The total area of greenhouse horticultural production has already reached 55.9 million square feet. About 20 percent of the operations in this region produce almost 50 percent of the revenue, with the majority of producers managing comparatively small operations, which are endemic in the Northeastern agricultural economy. This industry is thus critical to the health, expansion and sustainability of the rural economy in the Northeast.

Ornamentals are grown for their aesthetic value to consumers who have minimal tolerance for pest and disease damage. For this reason, chemical pesticides are used repeatedly to control many persistent pests and diseases, yet greenhouse and nursery growers' heavy reliance on chemical pesticides may not be sustainable. In fact, recent studies report increased resistance to pesticides in various herbivores and diseases, and chemical approaches to control are becoming ineffective (Mariyono 2008). The Environment Protection Agency pointed out that integrated pest management (IPM) is an effective and environmentally sensitive approach to pest control that can reduce growers' reliance on a chemical-based approach. IPM is not a single pest control method but rather employs a broad range of management practices including setting action thresholds, monitoring and identifying pests, practicing prevention, and implementing appropriate controls e.g., biological controls and bio-rational pesticides) and the judicious use of chemical pesticides when needed (Environment Protection Agency 2011).

Although greenhouse/nursery growers in the Northeast have expressed interest in IPM, little is known about the extent of IPM adoption in the region or the factors that facilitate or limit adoption. Thus, a systematic analysis of the factors affecting IPM implementation by growers of greenhouse and nursery crops in the Northeast is important to private and public decision makers interested in expanding IPM adoption.

We hypothesize that a variety of factors (e.g., size of greenhouse/nursery, growers' knowledge about and confidence in IPM, and the type of production problems a grower faces) influence adoption of IPM among greenhouse/nursery growers in three Northeastern states we surveyed. To test this, we surveyed 94 greenhouse/nursery growers in Maine, Vermont and New Hampshire. We then develop alternative measures of IPM adoption and employ discrete choice econometric models to assess factors influencing the likelihood of adopting IPM.

Our survey results show that Northeastern growers believe that IPM works better to control arthropod pests than diseases, and they are less likely to use IPM if they have serious disease problems. The unavailability of biological control agents and other IPM supplies limits growers' ability to adopt IPM. In addition, IPM adoption increases when the head grower makes the pest management decisions. We also find that larger operations which grow both ornamentals and vegetables are more likely to be IPM adopters.

Literature Review

IPM has received considerable attention in the agricultural economics literature. Many diverse aspects about IPM programs have been studied, including positive impacts of IPM on the environment (Dasgupta et al. 2007; Fernandez-Cornejo1996; Williams et al. 2005; Mullen et al. 1997; Trumble et al. 1997; Burkness et al. 2008; Bentley 2009) and on grower profitability (Trumble et al. 1997; Burkness et al. 2008; Fernandez-Cornejo1996; Dasgupta et al. 2007), positive consumers' attitudes toward IPM grown products (Govindasamy and Italia 1998, 2001; Florax et al. 2005), increased government support and investment in IPM programs (Templeton et al. 2010; Castle and Naranjo 2009), and efforts of extension programs to promote IPM adoption (White and Wetzstein 1995; Castle and Naranjo 2009; Mauceri et al. 2007; Ricker-Gilbert et al. 2008). Here we extend this literature by looking at the determinants of and approaches to measure IPM adoption applied in a non-food sector.

A few studies have examined how grower characteristics influence the decision to adopt IPM. Govindasamy (1998) demonstrates that risk-averse growers are less likely to adopt IPM. Other researchers have studied additional factors that influence growers' adoption of IPM. For example, Mahmoud and Shively (2004) argue that both access to IPM technology and IPM availability increase growers' adoption. Moreover, several studies show that such factors as farm size, gross sales, market destination, adopters' perceptions of IPM performance, and availability of labor are important determinants of IPM adoption (Fernandez-Cornejo et al. 1992).

Measuring adoption of IPM is not simple, and agricultural economists have employed several approaches for measurement. Earlier studies employed self-reported measures of IPM adoption and binary variables to distinguish conventional growers from those who use IPM. For example, Fernandez-Cornejo et al. (1992) classify growers as IPM when they use one or more IPM techniques. Dasgupta et al. (2007) characterize IPM growers as those practicing at least one method among biological control, light traps, organic production, crop rotation, manual clearing, and natural parasites. Other studies employ more elaborate measures of IPM adoption in which growers are classified into one of several categories depending on their usage of IPM tactics. Rickert-Gilbert et al. (2008), for instance, identify several IPM adoption levels for rice in Bangladesh and assign IPM growers into ‘simple’ (e.g., using disease resistant varieties), ‘intermediate’ (e.g., using trap systems) or ‘complex’ (e.g., using beneficial insects) categories.

The U.S Department of Agriculture’s (USDA) Economic Research Service (ERS) released a set of guidelines in 1994 with the goal of establishing a baseline estimate of IPM adoption and for monitoring progress toward policy adoption goals related to the expansion of sustainable production practices (Vandeman et al. 1994). These guidelines recognize that there is no universal definition of IPM. The report explains that IPM systems are highly variable, depending on the crop produced. IPM practices range from chemical- to biological-based along a continuum. The USDA approach divides growers into four categories, including “No IPM”, and three levels of adoption (Low, Medium and High), according to the number of practices considered under the umbrella of IPM methods. For example, in the USDA approach, a “low” level IPM grower scouts and applies pesticides according to thresholds for pests; a “medium” level IPM grower conducts “low” level activities plus one or two additional activities indicative of IPM; and a “high” level IPM grower employs additional IPM tactics more than their medium-level counterparts.

In summary, the literature suggests that IPM can increase profitability for some growers and reduce dependence on agrichemicals. Additionally, IPM requires important public investments in extension support and grower education, but in return is valued by consumers, and yields definable environmental benefits. In spite of strong public support to increase IPM adoption among ornamental industries in the Northeast, and growers' interest in the use of IPM, little is known about the extent of IPM adoption in the region among growers of non-food, high value greenhouse or nursery grown ornamentals or the factors that facilitate or limit adoption. To help fill this knowledge gap, we develop an empirical model and a set of hypotheses to study the factors that influence IPM adoption among this group of growers in three Northeastern states. We also extend the literature with some novel measures of IPM adoption. Most previous studies employed binary and categorical variables to measure IPM adoption. We extend those early models by employing a self-reported measure and a set of objective measures (binary, continuous and categorical) of IPM adoption.

The Survey Instrument

We developed a survey questionnaire to collect pertinent information regarding factors that facilitate (or hinder) adoption of IPM among greenhouse/nursery growers in Vermont, New Hampshire and Maine. We requested that the survey instrument be completed by the person responsible for making the pest management decisions for the greenhouse/nursery operation. Growers were asked to describe their greenhouse/nursery operations; rate the importance of various pest and disease problems in their crops; identify the management practices used;

select the kind of production system that best describes their operations (conventional versus IPM); assess the performance of IPM methods relative to conventional practices; and list the challenges that limit greater IPM adoption, including the use of biological control agents.

Earlier attempts to solicit information from growers indicate that they are weary of filling out surveys especially if there is no immediate direct benefit for them. To boost response rate, we used multiple methods for collecting data. Surveys were sent out to all greenhouse/ nursery growers on the Tri-state Greenhouse and Nursery IPM mailing list. Additionally, growers who attended IPM workshops held in the three target states in January 2009 (about 40 growers per state) are included in the survey list frame. Growers received incentives for attending the workshop and completing the survey, including a complimentary copy of the Greenhouse/Nursery Managers Guide to IPM in Northern New England, pesticide credits towards their pesticide applicator license, and the chance to win one of several door prizes donated by corporate sponsors. Finally, surveys were distributed at annual State Farm Shows, the New England Greenhouse Conference and during site visits to growers by Extension specialists and State Agriculture personnel.

Empirical Model

We employ four alternative strategies to measure IPM adoption. One is subjective (self-reported measure) and three were measures objective (binary, censored IPM score, and three-tiered). We employ these measures to identify factors that influence IPM adoption. These factors include the degree to which pests and diseases challenge the growers; the level of confidence growers have in IPM compared to conventional practices; growers' knowledge about IPM; the availability of biological control agents in the market; the diversity of the crops produced; the size of operation; the respondent's position; and the location of the operations. In general from, the empirical model is:

(1) *IPM ADOPTION= F [Pest Problems, Disease Problems, Grower Confidence, Grower Knowledge, Availability of Biological Control Agents, Revenue Source, Size of Operation, Position of Respondent, Location of Operation] .*

Dependent Variables: Measures of IPM Adoption

Based on information collected in the survey, we constructed four dependent variables to measure IPM adoption. The first is a self-reported indicator of IPM adoption (subjective measure). In the survey, we asked respondents whether IPM or "conventional control" best described the strategy to control for pests and diseases in the operation. We denote *Y_selfreport* as the subjective dependent variable, which is a dichotomous variable equal to one if the respondent states that he/she is an IPM grower and zero for those who consider themselves as users of conventional control technologies.

Objective measures, for their part, are based on a set of questions asking respondents which management practices describe the operation. Based on expert opinion (Lamb 2011) and borrowing from the principles of IPM described by the U.S. Environmental Protection Agency (EPA 2011), 36 IPM tactics from our survey questions could be classified into four types of activities: monitoring, pest identification, prevention and control (Figure 1).

[Figure 1 Here]

The first objective dependent variable, denoted as *Y_binary*, is a dichotomous variable which equals one for IPM growers, and zero otherwise. To be classified as an IPM grower, a respondent had to report using at least one activity from the “monitoring” list, one from the “pest identification” list, four from the “prevention” list and three from the “control” list (Lamb 2011). The other two objective measures of dependent variables are created on the basis of the above information.

The second objective dependent variable, denoted as *Y_IPMScore*, is a limited-continuous variable using IPM scores to represent grower’s degree of IPM adoption. Non-IPM growers have a score of zero, as defined by the binary variables above. For IPM growers, each respondent has an IPM score based on how many activities they use for “prevention” and “control”. According to Lamb (2011), “prevention” activities are twice as important as “control” activities, giving “prevention” a weight of 2/3, compared to “control” activities which are weighted 1/3. As shown in equation (2), the IPM score is calculated as 2/3 times the number of “prevention” activities plus 1/3 times the number of “control” activities. The higher the number of “prevention” and “control” activities, the higher the IPM scores. Thus, if a respondent is a conventional grower (i.e., when *Y_binary = 0*), then his/her IPM score is zero. To illustrate, if a respondent is an IPM grower and he/she uses eight activities from the “prevention” list and six from the “control” list, their IPM score is 2/3*8+1/3*6=7.33.

The third objective measure of IPM adoption divides respondents into three levels (Non-IPM grower, Low-IPM grower, High-IPM grower). This objective dependent variable, denoted as *Y_IPMlevel*, includes three levels: “0” for Non-IPM growers; “1”for Low-IPM growers; and “2” for High-IPM growers. Non-IPM growers are identified in the same way as for the binary objective measure. For IPM growers, according to their IPM scores calculated in the second objective measure, an IPM grower with a score below 9.3 is a Low-IPM grower, those above that score are High-IPM growers. We use 9.3 as the cutoff score between Low-IPM and High-IPM growers. This threshold corresponds to the score in which a grower practices at least two-thirds of the "prevention" and "control" activities. Growers with scores above 9.3 can be considered to have achieved a sufficiently high level of IPM adoption. Thus, a respondent with a score of 0 is a Non-IPM grower; one with a score of 6.3 (from the second objective measure) is classified as a Low-IPM grower; and one with a score of 10.3 is considered a High-IPM grower.

Explanatory Variables

The survey included questions pertaining to factors that influence IPM adoption as well as a number of relevant controls. We constructed three categories of explanatory variables, which take into account 1) the type of production problems, 2) the limitations or challenges for IPM adoption, and 3) the greenhouse/nursery characteristics.

In the survey, we asked 38 questions covering a wide range of diseases and pests (e.g., problems in greenhouse/nursery production). Respondents used three levels to rate the relevance of each problem as '1' (low importance), '2' (moderate importance) and '3' (high importance). Based on these responses, we created two variables to represent the relative importance of disease and pest problems: *DiseaseAvg* is the average rating of the 19 questions related to disease problems (e.g., anthracnoses, botrytis blight and crown gall), and *PestAvg* equals the average of the 19 questions related to insect and mite problems (e.g., aphids, black vine weevil, mealy bugs and fungus gnats). We hypothesize that greenhouse/nursery operations with more pest problems are less likely to adopt IPM than those with more disease problems. See the Appendix for the complete list of disease and pest problems.

We created three dichotomous variables to examine factors that may limit IPM adoption. The first variable, called *Unavailability,* captures the availability of IPM supplies, including biocontrol agents. *Unavailability* equals one if lack of availability of IPM supplies is a limiting factor for IPM adoption and zero otherwise. The second variable is *Unreliability*, which captures the degree of confidence in IPM to control pests, diseases and weeds. It equals one if IPM is considered unreliable and zero otherwise. The third variable is *Knowlimit*, which measures the level of IPM knowledge (e.g., pest biology and use of biological controls) and equals one if lack of knowledge is a limitation for IPM adoption, zero otherwise.

We control for greenhouse/nursery characteristics that may influence IPM adoption. We control for the size of operation using the number of full time workers (*Fullworker*).[1]
We note that area under cultivation is not a good measure of size because greenhouse/nursery operations often combine areas under protection and in the open, each with very different cultivation density. We also control for the production crop mix of the greenhouse/nursery operation. In particular, we create a variable reflecting the share of vegetable crops in total operation revenues (*PercentVeg*). One expects that a greater share of vegetables crops in total revenues is associated with higher IPM adoption, given that the literature suggest that consumers are willing to pay price premiums for IPM vegetables (e.g., Govindasamy and Italia 2001; Florax et al. 2005). We construct state dummies for New Hampshire (*NH*) and Maine *(ME)* to control for state differences. Finally, we construct a dichotomous variable called *headgrower*, which equals one if the survey respondent was the head grower and zero

otherwise (e.g., owner, worker). This is intended to control for the possibility that head growers may be more knowledgeable about the greenhouse/nursery operation, therefore providing more accurate survey responses.

Econometric Specifications

The empirical model consists of the following vector of explanatory variables and their corresponding coefficients:

(2) $\boldsymbol{X_i\beta} = \beta_0 + \beta_1 PestAvg_i + \beta_2 DiseaseAvg_i + \beta_3 Unavailability_i + \beta_4 Unreliability_i + \beta_5 Knowlimit_i + \beta_6 Headgrower_i + \beta_7 PercentVeg_i + \beta_8 Fullworker_i + \beta_9 NH_i,$

where *i* is the greenhouse/nursery operation. We employ four measures of IPM adoption, as explained above. Two of these measures, *Y_selfreport* and *Y_binary*, are dichotomous. Therefore, we obtain Logit parameter estimates using $\boldsymbol{X_i\beta}$ on the right hand side:

(3) $Y_i^* = \boldsymbol{X_i\beta} + \varepsilon_{1i}$,

where ε_{1i} is the *i.i.d.* error term and $Y_i = 1$ if $Y_i^* \geq 0$ and zero otherwise. Using the parameter estimates, the probability of being an IPM greenhouse/nursery operation is given by $Pr(Y=1) = exp(x\beta)/1 + exp(x\beta)$. We employ a Tobit model to estimate the regression with *Y_IPMScore* as dependent variable, given that this is a continuous dependent variable censored at zero. In mathematical notation, the Tobit model is specified as:

(4) $Y\_IPMScore_i^* = \boldsymbol{X_i\beta} + \varepsilon_{2i}$,

where ε_{2i} is the *i.i.d.* error term and $Y\_IPMScore_i = \boldsymbol{X_i\beta}$ if $Y\_IPMScore_i^* \geq 0$ and zero otherwise. Finally, we specify an Ordered Logit model for the specification with *Y_IPMlevel* as dependent variable. In mathematical notation:

(5) $Y\_IPMlevel_i^{*}=\boldsymbol{X_i\beta} + \varepsilon_{3i}$,

where ε_{3i} is the *i.i.d.* error term, $Y\_IPMlevel_i$ = 0 if $Y\_IPMlevel_i^{*} \leq 0$, $Y\_IPMlevel_i$ = 1 if $0 \leq Y\_IPMlevel_i^{*} \leq 9.3$, and $Y\_IPMlevel_i$ = 2 if $Y\_IPMlevel_i^{*} \geq 9.3$. The probabilities of being in a particular IPM level of adoption are $1\ /\ (1 + exp(x\beta - 0)\ )$, $1\ /\ (1 + exp(x\beta - 9.3)\ ) - 1\ /\ (1 + exp(x\beta - 0)\ )$ and $1 - (1 + exp(x\beta - 9.3))$ for $Y\_IPMlevel_i$ = 0, 1 and 2, respectively.

Data

A total of 96 responses were received, of which 94 useable responses were obtained. The descriptive statistics of the four dependent variables and the nine explanatory variables are presented in Table 1. The variable *Y_selfreport* has a mean of 0.58, as 54 of the 94 respondents reported that they have adopted IPM, the others considered themselves as conventional growers. The variable *Y_binary* has a mean of 0.62 which is slightly larger than the mean of *Y_selfreport*. According to this measure, 58 out of 94 respondents can be classified as “IPM growers”, while others are “Non-IPM growers”. The variable *Y_IPMlevel* has three categories, and the highest level is assigned a value 2. The mean of *Y_IPMlevel* is 0.71, which suggests that most respondents fall into the categories of Non-IPM and Low-IPM growers. For the continuous variable *Y_IPMScore*, the mean score is 4.41, and the maximum sample score is 11.30 (Table 1).

[Table 1 here]

We also present the definition of the explanatory variables and their descriptive statistics in Table 1. Production problems are likely to influence IPM adoption. The average score of pest-related problems is 0.85 and 0.75, for disease-related problems. The minimum score for the average pest problem is 0.05, showing that all the greenhouses/nurseries studied face pest problems to some degree. Among the three dummy variables describing growers' opinion about IPM, *Unreliability* (i.e., growers' lacking of confidence on the effectiveness IPM) has a larger sample mean in comparison to *Unavailability* and *Knowlimit*. This result suggests that, on average, growers may not be confident about the effectiveness of IPM. The greenhouses/nurseries in our sample derived, on average, 15.7 percent of their income from vegetable crops and employed three to four full-time workers. Just over a third of the respondents were in charge of decisions on IPM, and 19.2 percent of the greenhouse/nursery operations were located in New Hampshire.

Results

In Table 2 and 3 we present regression results for the models with *Y_binary*, *Y_IPMScore*, *Y_selfreport* and *Y_IPMlevel* as dependent variables, including the estimated coefficients and their marginal effects. We discuss the parameter estimates of each model below.

Regression 1: IPM Binary Measure—Logistic Model

The Wald test indicates that the model is overall significant and the pseudo R-squared suggests that the model explains about a third of the variability in the dependent variable. Columns 1 and 2 in Table 2 present the estimated coefficients and marginal effects of the explanatory variables for *Y_binary*. Regarding the nature of production problems, the coefficient of *DiseaseAvg* is positive and significant, suggesting that greenhouses/nurseries with more disease problems are less likely to adopt IPM. The marginal effect indicates that a one-unit increase in *DiseaseAvg* decreases the probability of IPM adoption by 54.3 percent. The coefficient of *PestAvg* is positive, as expected, but statistically insignificant.

[Table 2 Here]

Next, we consider the types of limitations to IPM adoption. The coefficient of *Unavailability* is negative and significant, indicating that unavailability of biological control agents and other IPM supplies results in a 51.6 percent decrease in the probability of IPM adoption. The coefficient of *Unreliability* is negative, as expected, but statistically insignificant; and the coefficient of *Knowlimit* is statistically insignificant.

The coefficient of *PercentVeg* is positive and statistically significant. Specifically, a one percentage point increase in the share of revenue derived from vegetables increases the probability of IPM adoption by 0.5 percent. This is expected, given that vegetable growers have more incentives to use IPM to grow vegetables, and this facilitates the transfer of skills to other crops. Our results also show that size of operation, measured as the number of full-time workers (*Fullworker*) has a significant effect on IPM adoption: a one-level increase in the number of full-time workers increases the probability of IPM adoption by 22.7 percent. Having a larger labor force seems to facilitate IPM adoption because this production system tends to be more labor intensive than conventional production. The coefficient for *Headgrower* is positive and significant. Head growers tend to be more familiar with the production practices, and the significant coefficient on *Headgrower* may reflect their ability to respond to the survey with more precision. The coefficient of *NH* is positive but statistically insignificant, indicating no differences in IPM adoption across the three states in the sample.[2]

Regression 2: IPM Scores Measure—Tobit model

Columns 3 and 4 in Table 2 show the Tobit parameter estimates and their marginal effects using *Y_IPMScore* as the dependent variable. The *F-test* shows that the model is significant at the one percent level. In general, the parameter estimates are similar to those for the logit model discussed above, but the results are more robust in some cases. In particular, the positive, significant coefficient on *PestAvg* indicates that greenhouses/nurseries with more pest problems are more likely to adopt IPM. The marginal effect indicates that a one unit increase in pest problem score is associated with a 5.65 increase in the IPM score. As with the logit model results, the coefficient on *DiseaseAvg* is negative and significant; the results show that a one point increase in disease problem scores is associated with a 5.52 decrease in the IPM score. Our results for the factors that may limit IPM adoption are similar to those in the logit model (Regression 1) as well. That is, lack of availability of biological control agents and other IPM supplies is associated with a 3.45 decrease in IPM adoption scores; and the coefficient on *Unreliability* and *Knowlimit* are both statistically insignificant.

The coefficient on *PercentVeg* is statistically significant and indicates that a one percentage point increase in the revenue derived from vegetable crops is associated with a 0.034 increase in IPM adoption score. Similar to the logit case, the number of full time workers and the position of the respondent influence IPM adoption: a one-level increase in the number of full-time workers raises the IPM score by 1.80 points; and IPM adoption scores were 2.61 points higher when the respondent is the head grower. Finally, similar to the Logit specification, the coefficient of *NH* is positive, but significant in this model specification, suggesting that greenhouses/nurseries in New Hampshire have an average IPM score 1.68 points higher than Maine and Vermont.

Regression 3: IPM self-report Measure—Logistic Model

Here we explore whether the results change when the dependent variable is a self-reported measure of IPM adoption. Because the dependent variable *Y_selfreport* is binary, we employ the logistic method for estimation (Table 2, Columns 5 and 6). The overall model is only significant at the 12 percent level (Prob>Chi^2=0.12) and the pseudo R-squared suggests that this model explains about one fourth of the variability of the dependent variable.

The two variables pertaining to the type of production problems (*DiseaseAvg* and *PestAvg*) become insignificant in this specification. Regarding the IPM adoption challenges, contrary to the models using objective measures of adoption, the coefficients of *Unreliability* and *Knowlimit* are negative and significant. The parameter estimates suggest that unreliability is associated with a 22.8 percent reduction in the probability of IPM adoption; limited knowledge results in a 62.8 percent decrease in adoption probability. In contrast, the coefficient estimated for *Unavailability* is not statistically significant. The estimated coefficients for *PercentVeg* and *Fullworker* are both positive but statistically insignificant. The coefficient of the state dummy, *NH*, is negative and significant; the marginal effect indicates that greenhouses/nurseries in New Hampshire have a 39.1 percent higher probability of adopting IPM than those in Vermont and Maine.

Regression 4: Objective IPM Adoption in Levels

In this regression the *Y_IPMlevel* takes three values: Non-IPM, Low-IPM and High-IPM. The Wald test indicates that the null hypothesis of all coefficients being equal to zero is rejected at the 1.5 percent level of significance. Table 3 presents the estimated coefficients, log odd ratios and their corresponding marginal effects.

[Table 3 Here]

The coefficient of *PestAvg* has a positive effect on IPM adoption, and its log odds ratio is 49.72. This indicates that with a one unit increase in the average pest problem score, the odds of a greenhouse/nursery being in a higher IPM level is 49.72 times greater than being in a lower IPM level. Conversely, *DiseaseAvg* has a significant negative influence on IPM adoption. Its odds ratio is 0.03, indicating that a one unit increase in the average disease score decreases the odds of being in a higher level of IPM category by 97.1 percent. These results are similar to those in the models using objective measures of IPM adoption (Regressions 1 and 2).

The coefficient of *Unavailability* is negative and statistically significant. The odds ratio indicates that limited availability of IPM supplies and biological control agents increase the odds of being in a lower IPM level by 93.3 percent. However, the coefficients of *Unreliability* and *Knowlimit* are statistically insignificant. The coefficient of *Fullworker* exhibits a significant and positive effect on the level of IPM adoption. The log odds ratio indicates that with a one level increase in the number of full time workers, the odds of being in a higher IPM level category increases by 203 percent. The estimated coefficient of *Headgrower* is positive and statistically significant; its log odds ratio indicates that if a respondent is a head grower, then the greenhouse/nursery is 3.061 times more likely to move to a higher level of IPM.

The marginal effects shown in Table 3 also contribute to our analysis of factors affecting IPM adoption. For example, a one unit increase in the number of full-time workers decreases the probability of being in the Non-IPM level by 21.1 percent; and increases the probability of being in the Low-IPM and High-IPM levels by 18.1 and 3.0 percent, respectively. In addition, the results suggest that a one point increase in disease problem scores increases the probability of being in the Non-IPM level by 67.3 percent. At the same time this decreases the probability of being in the Low-IPM and High-IPM level by 57.7 percent and 9.6 percent respectively.

As discussed above, the effects of changes for average pest problems are opposite to those associated with changes in disease problems. A one point increase in pest problem scores decreases the probability of being in the Non-IPM level by 74.5 percent, increases the probability of being in the Low-IPM level by 63.9 percent, and increases the probability of being in the High-IPM level by 10.7 percent. These marginal effects are consistent with our odds ratios discussion, but provide an additional level of detail regarding the factors that influence IPM adoption.

Summary of results

Our results suggest that disease and pest problems influence IPM adoption. Greenhouse/nursery operations facing significant disease problems are less likely to adopt IPM, whereas those with serious pest problems are more likely to use IPM. On the other hand, our results suggest that a lack of availability of biological control agents and other IPM supplies dampens IPM adoption among Northeastern greenhouse/nursery growers. Greenhouse/nursery growers that also produce vegetables are more likely to adopt IPM than those growing only ornamentals. Furthermore larger greenhouse/nursery operations (measured as the number of full-time workers) exhibit higher levels of IPM adoption.

The models with objective measures as dependent variables (*Y_binary, Y_IPMScore, and Y_IPMlevel*) provide similar results regarding factors influencing IPM adoption. However, we identify substantial differences between these three models and the model that uses a self-reported adoption measure (*Y_selfreport*). The coefficient of *Fullworker, DiseaseAvg* and *Unavailability* all show significant effects on IPM adoption in the models using objective measures as dependent variables. In contrast, they become statistically insignificant when using the self-reported measure as the dependent variable. In addition, the coefficients of *Unreliability* and *Knowlimit* are not statistically significant in the models using objective measures, but are statistically significant when using the self-reported IPM adoption measure.

Conclusion

This study examined factors that limit or facilitate IPM adoption among growers of greenhouse/nursery products in the Northeast. Given the recent attention to IPM production methods favored by growers and the public with an interest in sustainability, the findings of this study may contribute to ongoing efforts to promote IPM adoption.

The differences between self-reported and objective measures imply that greenhouse/nursery growers may require more knowledge about IPM. The university extension system can play a critical role here, and its specialists and educators can use the classification proposed in this study to develop training programs targeted at enhancing growers' knowledge of IPM. Another important finding of our study is that larger, diversified greenhouses/nurseries are more likely to adopt IPM. This does not mean that extension programs should solely target larger operations to enhance IPM adoption. Instead, extension programs should work with small and large operations alike to encourage IPM implementation. Smaller operations may require more help from extension specialists to make progress towards wider use of IPM; and larger operations can be used to demonstrate the benefits of IPM adoption because they tend to be early IPM adopters. IPM Extension specialists and educators should also expect to find that greenhouses/nurseries which face serious disease problems are less likely to use the IPM methods, so those greenhouses/ nurseries are less likely to be IPM adopters.

We also find that unavailability of biological control agents is an important limiting factor to IPM adoption. Suppliers of IPM technology have a role to play in addressing this limitation. They could widely broadcast their products to ensure growers can make informed decisions on acquisition of biological control agents and their suitability for dealing with specific pests. At the same time, lack of confidence in IPM controls for pests and disease could also limit IPM adoption. Therefore, IPM suppliers may also need to refine their technologies to enhance the reliability of IPM. Cooperation with Extension and research programs can be useful to IPM suppliers. Extension specialists interact frequently with large numbers of grower networks and can provide advice regarding appropriate information about where to get IPM supplies. In addition, cooperation with research universities could enhance the reliability of IPM; for example, alternative IPM tactics may be appropriate for different stages in the plant growth cycle.

We find substantial differences between objective and self-reported measures of adoption. This suggests that growers and policy makers may think of IPM standards differently. Self-reported IPM measures could lack objectivity and, if this is true, it may lead to biased impressions of IPM adopters; this may be due to financial incentive programs used by state governments to promote IPM adoption and to possible price premiums for IPM-labeled products. Regulators should maintain strict surveillance of products labeled as IPM. Surveillance, in turn, should include setting standards, monitoring production processes and establishing commodity traceability systems. At the same time, this may be costly and may raise concerns about the efficiency of financial incentives for IPM.

While this study provides valuable insights on factors influencing IPM adoption, it has some limitations that require further investigation. For example, future research should conduct cost-benefit analyses of operations using IPM and conventional methods in the greenhouse/nursery sectors to conduct rigorous comparative studies. Another issue is that our sample of greenhouses/nurseries may suffer from selection bias, given that the surveys were mailed to growers that participated in an IPM workshop. These growers may be more interested in, or at least better informed on, IPM methods. Future survey-based research should address this issue by mailing the IPM survey randomly to all greenhouse/nursery operations, not just to the greenhouses and nurseries that expressed an interest in adopting IPM methods.

References

Bentley, W.J. 2009. “The Integrated Control Concept and Its Relevance to Current Integrated Pest Management in California Fresh Market Grapes.” *Pest Management Science* 65(12): 1298-1304.

Burkness, E.C., and W.D. Hutchison. 2008. “Implementing Reduced-Risk Integrated Pest Management in Fresh-Market Cabbage: Improved Net Returns via Scouting and Timing of Effective Control.” *Journal of Economic Entomology* 101(2): 461-471.

Castle, S., and S.E. Naranjo. 2009. “Sampling Plans, Selective Insecticides and Sustainability: the Case for IPM as 'Informed Pest Management.” *Pest Management Science* 65(12): 1321-1328.

Dasgupta, S., C. Meisner, and D. Wheeler. 2007. “Is Environmentally Friendly Agriculture Less Profitable for Growers? Evidence on Integrated Pest Management in Bangladesh.” *Review of Agricultural Economics* 29(1): 103-118.

Fernandez-Cornejo, J.E., D. Beach, and W.Y. Huang. 1992. “The Adoption of Integrated Pest Management Technologies by Vegetable Growers.” *ERS staff report* No. AGES 8228. USDA, Washington, D.C.

Fernandez-Cornejo, J.E. 1996. “The Microeconomic Impact of IPM Adoption: Theory and Application.” *Agricultural and Resource Economics Review* 25(2): 149-160.

Florax, R.J.G.M., C.M. Travisi, and P. Nijkamp. 2005. “A Meta-Analysis of the Willingness to Pay for Reductions in Pesticide Risk Exposure.” *European Review of Agricultural Economics* 32(4): 441-467.

Govindasamy, R., and J. Italia. 1998. “A Willingness-to-Purchase Comparison of Integrated Pest Management and Conventional Produce.” *Agribusiness* 14(5): 403-414.

Govindasamy, R., J. Italia, and A.O. Adelaja. 2001. “Predicting Willingness-to-Pay a Premium for Integrated Pest Management Produce: A Logistic Approach.” *Agricultural and Resource Economics Review* 30(2):151-159.

Lamb, E.M. 2011. Ornamental IPM Coordinator of the New York State Integrated Pest Management Program, series of personal interviews in the spring 2011.

Mahmoud, C., and G. Shively. 2004. “Agricultural Diversification and Integrated Pest Management in Bangladesh.” *Agricultural Economics* 30(3): 187-194.

Mariyono, J. 2008. “Farmers' Economic Tolerance toward Pest Infestations: Impact of Integrated Pest Management Training in Indonesia.” *Quarterly Journal of International Agriculture* 47(1): 61-73.

Mauceri, M., J. Alwang,G. Norton, and V. Barrera. 2007. “Effectiveness of Integrated Pest Management Dissemination Techniques: A Case Study of Potato Growers in Carchi, Ecuador.” *Journal of Agricultural and Applied Economics* 39(3): 765-780.

Mullen, J.D., D.W. Reaves, and G.W. Norton. 1997. “Economic Analysis of Environmental Benefits of Integrated Pest Management.” *Journal of Agricultural and Applied Economics* 29 (2): 243-253.

Ricker-Gilbert, J., G.W. Norton, J. Alwang, M. Miah, and G. Feder. 2008. “Cost-Effectiveness of Alternative Integrated Pest Management Extension Methods: An Example from Bangladesh.” *Review of Agricultural Economics* 30(2): 252-269.

Templeton, D.J., and N. Jamora. 2010. “Economic Assessment of a Change in Pesticide Regulatory Policy in the Philippines.” *World Development* 38(10):1519-1526.

Trumble, J.T., G.S. Kund, and W.G. Carson. 1997. “Economics and Environmental Impact of a Sustainable Integrated Pest Management Program in Celery.” *Journal of Economic Entomology* 90 (1): 139-146.

U.S. Environmental Protection Agency. 2011. “Health and Safety Fact Sheets: Integrated Pest Management Principles.” Washington, D.C. Available online at http://www.epa.gov/pesticides/factsheets/ipm.htm (accessed September 8, 2010).

U.S, Department of Agriculture, National Agricultural Research Service, Census of Horticultural Specialties. 1998. Washington, D.C. Available online at http://www.agcensus.usda.gov/Publications/1997/Horticulture_Specialties/index.asp (accessed August 5, 2010).

U.S, Department of Agriculture, National Agricultural Research Service, Census of Horticultural Specialties. 2009.Washington, D.C. Available online at http://www.agcensus.usda.gov/Publications/2007/Online_Highlights/Census_of_Horticulture/index.asp(accessed August 5, 2010).

Vandeman, A., J.E. Fernandez-Cornejo, S. Jans, and B.H. Lin. 1994. “Adoption of Integrated Pest Management in U.S. Agriculture.” Agricultural Information Bulletin 707. USDA, Washington, D.C (accessed November 8, 2010)

Williams, G.M., R.B. Leidy, C. Schal, H.M. Linker, and M.G. Waldvogel. 2005. “Comparison of Conventional and Integrated Pest Management Programs in Public Schools.” *Journal of Economic Entomology* 98(4): 1275-1283.

White, F.C., and M.E. Wetzstein. 1995. "Market Effects of Cotton Integrated Pest Management." *American Journal of Agricultural Economics* 77(3): 602-612.

Figure 1. Four Key Components of an IPM Program

Group 1:

Monitoring
pest monitoring

Activities:
Sticky cards
Indicator plants
Regular scouting
Hire commercial scout
Use deg. days to track pests
Foliar testing

Group 2:

Pest Identification
accurate pest identification

Activities:
Identify pests/diseases yourself
Professional insect/disease ID
Use disease test kits
Send plants out for disease testing

Group 3:

Prevention
manage the crop to prevent pests from becoming a threat

Activities:
Screen vents
Crop rotation
Inspect new plant shipments
Disinfect growing areas
Sanitize pots or use new ones
Sanitize soil or use new soil
Reemay plant covering
Culture indexed plants
Fallow crop space
Use DIF
Cover floor with weed cloth
Pest resistant varieties
Drip irrigation
Remove weeds
Recycle water
Soil testing
Water testing

Group 4:

Control
evaluate the proper control method so that appropriate method could be taken

Activities:
Rotate pesticide classes
Release predators, parasites, nematodes
Spray insecticides on floor/benches
Use pesticides less toxic to beneficial
Use pesticides with short residual activity
Use microbial biocontrol (fungi, bacteria)
Preventative pesticide treatment
Spot pesticide treatment
Use chemical pesticides

Source: U.S. Environmental Protection Agency (2011)

Variables	Description	Mean	StdDev	Min	Max
Dependent Variables					
Y_selfreport	Self-reported as IPM grower (yes=1, no=0)	0.575	0.497	0	1
Y_binary	Objective measure of IPM grower (yes=1, no=0)	0.617	0.489	0	1
Y_IPMScore	IPM score each grower could get	4.411	3.834	0	11.3
Y_IPMlevel	Three IPM levels each grower could rank	0.713	0.633	0	2
Independent Variables					
Headgrower	Position of respondent in the operation (yes=1, no=0)	0.34	0.476	0	1
PercentVeg	Percentage of total revenue from growing vegetables	15.691	25.331	0	100
Fullworker	Level of hired full-time worker in the operation	2.588	1.482	1	5
NH	Location of business in New Hampshire (yes=1, no=0)	0.192	0.396	0	1
PestAvg	Degree of pest challenges faced by greenhouse and nursery growers	0.85	0.512	0.1	2.3
DiseaseAvg	Degree of disease challenges faced by greenhouse and nursery growers	0.758	0.564	0	2.1
Unavailability	1 if to order biological control agents is a great Hindrance; 0 otherwise	0.128	0.336	0	1
Unreliability	1 if lacking of confidence in the reliability of IPM is a great hindrance to implement them; 0 otherwise	0.468	0.502	0	1
Knowlimit	1 if knowledge limit of IPM measure is a great hindrance to implement them; 0 otherwise	0.149	0.358	0	1

Table2. Regression Results for Objective Measure of IPM[a]

Variables name	Binary IPM Measure *Logit model* Coefficient (std err)	Marginal Effect	IPM Scores *Tobit model* Coefficient (std err)	Marginal Effect	IPM Self-report *Logit model* Coefficient (std err)	Marginal Effect
Constant	-2.693*** (1.506)		-3.181* (1.952)		1.271* (0.857)	
PestAvg	2.704 (1.955)	0.575	5.750** (3.021)	5.654	-1.258 (1.527)	-0.173
DiseaseAvg	-2.551* (1.635)	-0.543	-5.613** (2.730)	-5.520	-1.786 (1.502)	0.246
Unavailability	-2.351** (1.246)	-0.516	-3.446** (2.007)	-3.446	0.850 (1.397)	0.087
Unreliability	-0.795 (0.58)	-0.188	-0.894 (1.071)	-0.894	-1.187*** (0.595)	-0.228
Knowlimit	1.128 (1.301)	0.181	2.297 (2.135)	2.297	-3.316** (2.054)	-0.628
Headgrower	1.469** (0.566)	0.214	2.614*** (1.009)	2.614	-0.290 (0.539)	-0.044
PercentVeg	0.024*** (0.014)	0.005	0.035*** (0.016)	0.034	0.0004 (0.012)	0.0005
Fullworker	1.068*** (0.473)	0.227	1.831*** (0.411)	1.801	0.024 (0.195)	0.003
NH	1.113 (0.821)	0.180	1.678* (1.139)	1.678	-1.849*** (0.715)	-0.391
# Observations	72		72		72	
Log Pseudo likelihood	-31.944		-152.088		-37.648	
Wald Chi2/F	19.84		5.47		14.01	
Prob> Chi2/F	0.019		0.000		0.122	
Pseudo R2	0.313		0.100		0.235	

Note: *, **, ***denote coefficient estimates statistically significant at the 0.15, 0.10, and 0.05 level, respectively. Standard errors are presented in parentheses. Each variable is defined in Table 1.

[a] the number of observations in those models is 72 instead of 94 because some values are missing when constructing the independent variables.

Table 3. Ordered Logistic Regression Results and its Marginal Probability Effects

	Three IPM Levels[a]				
Variable name	Coefficient (std err)	Log odds Ratios	Non-IPM grower IPM Value=0 (Marginal Effects)	Low-IPM grower IPM Value=1 (Marginal Effects)	High-IPM grower IPM Value=2 (Marginal Effects)
Constant	-3.181* (1.952)				
PestAvg	3.906* (2.390)	49.716*	-0.745** (-0.385)	0.639** (0.351)	0.107 (0.077)
DiseaseAvg	-3.530** (1.911)	0.029**	0.673* (-0.300)	-0.577* (0.276)	-0.096 (0.067)
Unavailability	-2.697** (1.149)	0.067**	0.587* (-0.186)	-0.555* (0.187)	-0.032 (0.022)
Unreliability	-0.393 (0.543)	0.675	0.075 (-0.108)	-0.0649 (0.094)	-0.011*** (0.015)
Knowlimit	1.634 (1.463)	5.125	-0.221** (-0.116)	0.136* (0.059)	0.085 (0.135)
Headgrower	1.119*** (0.513)	3.061***	-0.196** (-0.102)	-0.160** (-0.087)	0.037 (0.027)
PercentVeg	0.012 (0.009)	1.012	-0.002 (-0.002)	-0.002 (0.002)	0.0003 (0.000)
Fullworker	1.109*** (0.396)	3.030***	-0.211* (-0.053)	0.181* (0.057)	0.030** (0.017)
NH	0.707 (0.548)	2.209	-0.12 (-0.090)	0.095 (0.069)	0.024 (0.026)
# Observations	72				
Log Pseudo likelihood	-45.814				
Wald Chi2/F	20.55				
Prob> Chi2/F	0.015				
Pseudo R2	0.289				

Note: *, **, ***denote coefficient estimates statistically significant at the 0.15, 0.10, and 0.05 level, respectively. Standard errors are presented in parentheses. Each variable is defined in Table 1.
Marginal probability effects are estimated at sample means.
[a]Three levels of IPM growers include: (1) Non-IPM grower (value=0), (2) Low-IPM grower (value=1), (3) High-IPM grower (value=2).

Appendix

Below is a list of 19 disease problems and 19 insect and mite problems from the survey.

Disease Problems (19 questions):
Anthracnoses
Bacterial leaf spots or cankers
Botrytis blight
Canker diseases
Crown gall
Damping off
Downy mildews
Fungal leaf spots
Fusarium wilt
Phytophthora root, stem or crown rots
Powdery mildew
Pythium root, stem or crown rots
Rhizoctonia root, stem rot or blight
Rust diseases
TSWV/INSV(thrips-vectored viruses)
Verticillium wilt
Black root rot – *Thielaviopsis*
Other(specify)
Other(specify)
Pest Problems (19 questions)
Aphids
Black vine weevil
Cyclamen mites
Broad mites
Fungus gnats
Lace bugs
Leaf feeding beetles
Leaf feeding caterpillars
Leafhoppers
Leafminers
Mealybugs
Scales
Shore flies
Spider mites and other mites
Thrips
White grubs
Whiteflies
Other (specify)
Other (specify)

[1] The survey includes five levels capturing labor use:‘1’is less than one full-time worker;‘2’, between 1 and 2 full-time workers;‘3’, between 3 and 4 full-time workers;‘4’, between 5 and 6 full-time workers; and ‘5’, over 6 full time workers.

[2] We dropped the state dummy for Maine (ME) because its coefficient is statistically insignificant in all models and because the need to preserve enough degrees of freedom given the small size of our sample.

OTHER A.E.M. WORKING PAPERS

WP No	Title	Fee (if applicable)	Author(s)
2011-18	Urban Agglomeration Economies in the U.S. Greenhouse and Nursery Production		Gómez, M.
2011-17	Evaluating the Impact of the Fruit and Vegetable Dispute Resolution Corporation on Regional Fresh Produce Trade among NAFTA Countries		Gómez, M., Rizwan, M. and N. Chau
2011-16	Does the Name Matter? Developing Brands for Patented Fruit Varieties		Rickard, B., Schmit, T., Gómez, M. and H. Lu
2011-15	Impacts of the End of the Coffee Export Quota System on International-to-Retail Price Transmission		Lee, J. and M. Gómez
2011-14	Economic Impact of Grapevine Leafroll Disease on Vitis vinifera cv. Cabernet franc in Finger Lakes Vineyards of New York		Atallah, S., Gomez, M., Fuchs, M. and T. Martinson
2011-13	Organization, Poverty and Women: Andhra Pradesh in Global Perspective		Dev., S., Kanbur, R. and G. Alivelu
2011-12	How have agricultural policies influenced caloric consumption in the United States?		Rickard, B., Okrent, A. and J. Alston
2011-11	Revealing an Equitable Income Allocation among Dairy Farm Partnerships		Dressler, J. and L. Tauer
2011-10	Implications of Agglomeration Economics and Market Access for Firm Growth in Food Manufacturing		Schmit, T. and J. Hall
2011-09	Integration of Stochastic Power Generation, Geographical Averaging and Load Response		Lamadrid, A., Mount, T. and R. Thomas
2011-08	Poor Countries or Poor People? Development Assistance and the New Geography of Global Poverty		Kanbur, R. and A. Sumner
2011-07	The Economics of Africa		Aryeetey, E., Devarajan, S., Kanbur, R. and L. Kasekende
2011-06	Avoiding Informality Traps		Kanbur, R.

Paper copies are being replaced by electronic Portable Document Files (PDFs). To request PDFs of AEM publications, write to (be sure to include your e-mail address): Publications, Department of Applied Economics and Management, Warren Hall, Cornell University, Ithaca, NY 14853-7801. If a fee is indicated, please include a check or money order made payable to Cornell University for the amount of your purchase. Visit our Web site (*http://aem.cornell.edu/research/wp.htm)* for a more complete list of recent bulletins.