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Estimating Insecticide Application Frequencies: A Comparison of Geometric and Other Count Data Models

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ABSTRACT

The number of insecticide applications made by an apple grower to control an insect infestation is modeled as a geometric random variable. Insecticide efficacy, rate per application, month of treatment, and method of application all have significant impacts on the expected number of applications. The number of applications to control a given insect population is dependent on the probability of achieving successful control with a given application. Results suggest that northeastern growers have the highest and mid-Atlantic growers the lowest probability of controlling an infestation with a given application. Results also indicate that scales require the least and moths the most number of applications. Growers are not responsive to per unit insecticide prices, but respond negatively to insecticide toxicity, supporting findings from previous pesticide demand analyses.

Key Words: apples, count data, geometric, insect control, pesticides.

Data on the use of insecticides are often treated as continuous when in fact they result from a series of discrete choices and processes. Farmers must decide whether to apply insecticides, which insecticides to apply (given the decision to apply is made), and how many times to apply the selected insecticides. The decision to apply insecticides for treatment of a given pest infestation is a binary decision, often based on a previously determined treatment threshold. Active ingredient choice is a qualitative variable (setting the recommended application rate as well as the levels of other attributes), and the datum of interest for this analysis, application frequency,[1] is a discrete variable which takes only strictly positive integer values. Total use of insecticides, and thus total potential for offsite environmental contamination, depends on the results of a combination of discrete and continuous decisions made by the grower throughout the season.

Good estimates of the determinants of insecticide application frequencies are needed to understand how farmers alter chemical insect control decisions to reflect differences in insecticide productivity, pest management practices, and environmental concerns. The number of insecticide applications is difficult to assess and estimate because it involves both ex ante utility-maximizing objectives of grow-

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[1] The application frequency is defined here as the number of applications to treat a given infestation, not the total number of applications made over the course of a season.

ers and unknown random elements. The observed number of applications is the result of a random process conditioned on levels of exogenous variables and variables selected by the grower prior to initial application of insecticides. Farmers can influence the expected application frequency through their choices of active ingredient types, rates, and pest management strategies, but they cannot choose, a priori, the final number of applications that will be required to manage an infestation. The determination of the application frequency variable has large consequences for total insecticide use in some crops, including apples and other fruits and vegetables, as total insecticide use to manage a given infestation will be the frequency of application times the rate per application. Application frequency thus has a multiplicative effect on observed total quantities of insecticides used, amplifying environmental exposure to insecticide externalities.

Many farmers use some form of treatment threshold to determine when application of insecticides can be economically justified (Headley). These treatment thresholds are not directly observable to the analyst, but are established by the farmer based on some rule (not necessarily profit maximization), or obtained from private consultants or extension professionals. The threshold will be based on observable variables such as intended markets, output prices, insecticide costs, application costs, and information on relative damage associated with different insects, both to yield and to produce quality, provided by extension and pesticide industry professionals (Marra, Gould, and Porter). Treatment thresholds may also reflect the grower's level of risk aversion. Because the treatment threshold depends in part on the target insect and the active ingredient applied, there will be a treatment threshold associated with each active ingredient for each insect type. The treatment threshold for a given insect type is determined through the farmer's selection of an active ingredient.[2] Insecticide applications are made whenever the target insect population exceeds the treatment threshold population, and continue until the insect population falls below the threshold level.

The remainder of this article is devoted to the development and estimation of models of insecticide application frequencies, taking into account the nonnegative, nonzero integer nature of application frequency data. A new estimator, based on the geometric distribution, is developed and estimated. It is demonstrated that the geometric distribution of application frequencies is theoretically consistent with the use of treatment thresholds in the determination of insecticide use. The geometric model also allows for estimation of the probability of successfully managing an insect infestation with a given application, thereby allowing for analysis of the effectiveness of insecticide applications across regions and insect types. For comparison, traditional count data models, including the truncated Poisson and truncated negative-binomial, also are estimated. The empirical implementation of the models examines the impacts of insecticide efficacy, severity of infestation, integrated pest management (IPM) practices, environmental and health factors, and economic variables on the expected number of applications and the probability of successful control.

The Model

During the course of a season, an apple grower may face numerous infestations with a variety of insect pests.[3] A farmer may make multiple applications as part of a treatment program for a particular pest. The number of applications made in a particular treatment i, N_i, is the result of a series of discrete choices made based on comparing observed target insect populations with target insect population thresholds at a discrete number of evaluation points. Define $\bar{I}_{jmt}$ to be the treatment threshold for insect type j and active ingredient m at evaluation point t during the season. An evaluation point

[2] A model of insecticide active ingredient selection is developed and estimated in Hubbell.

[3] An infestation is defined here as an occurrence of a population of insects high enough to warrant an initial application with an insecticide.

is defined as any time at which the grower receives new information on levels of target insects in the field. This information can come from personal observations, professional scouts, or extension announcements of regional infestations. The treatment threshold may change throughout the season as growers receive new information on weather and market conditions. If farmers take into account health and environmental impacts, treatment thresholds also may depend on implicit environmental and health costs associated with use of insecticides (Moffitt; Beach and Carlson; Higley and Pedigo).

Defining $\boldsymbol{H}$ to be a vector of economic variables and $\boldsymbol{Z}_m$ to be a vector of attributes associated with active ingredient m, the expected utility-maximizing treatment threshold for insect type j and active ingredient m is

$$(1) \qquad \bar{I}_{jmt} = \bar{I}(j, Z_m, H_t), \qquad j = 1, \ldots, J,$$

where J equals the total number of possible target insects on apples. The grower will have a treatment threshold associated with each of the J possible target insects for each active ingredient, for a total of JM potential thresholds at each evaluation point t, where M is the number of active ingredients. A standard specification for the threshold function is

$$(2) \qquad \bar{I}_{jmt} = C_{jm}/V_t L_m D_m K_{jm},$$

where C_{jm} is the cost of an application for insect j with insecticide m (this can include environmental and health costs), V_t is the expected value of the crop at time t, L_m is the loss in units of output per insect, D_m is damage per loss unit, and K_{jm} is the proportionate reduction in damage from insect j from application of insecticide m (Higley and Pedigo).

Because the variables on the right-hand side of (2) are not easily measurable, $\bar{I}_{jmt}$ is in general an unobservable latent variable to an outside analyst, but the active ingredients and number of applications made by the grower during a particular treatment are observable, ex post. Growers can measure pre- and post-application insect populations and compare them with their selected treatment thresholds, but this information is generally not observed by outside analysts. Once growers have made the initial decision to apply insecticides, they are faced with a series of choices based on information received concerning the insect population, as well as crop growth and market conditions. At each decision point, the grower must choose whether to make an application with the same chemical, make an application with a different chemical, or stop making applications. The grower will make an application with the same chemical if the observed insect population is greater than or equal to the threshold population and the degree of effectiveness from the application meets some optimality criteria. The grower will make an application with a different chemical if the observed insect population is greater than or equal to the threshold population but the effectiveness of the chemical does not meet the optimality criteria. The grower will stop making applications if the insect population falls below the treatment threshold. The final number of applications is the result of repeated applications of this decision rule made by the grower in response to observed insect populations and optimal threshold levels. Define δ_t to be an indicator variable equal to one if the grower makes an application at evaluation point t, and zero otherwise. The total number of applications during treatment i is calculated as

$$(3) \qquad N_i = \sum_{t+1}^{T_i} \delta_t, \qquad \delta_t = 0, 1,$$

where T_i is the number of evaluation points during treatment i.

In statistical terms, the grower can be thought of as conducting a series of trials until a success (defined here as successful management of the infestation to below the treatment threshold) occurs. The probability of success with any particular application, θ_t, is a function of the productive attributes of the insecticide, the target insect type, the initial target insect population, the susceptibility of the insect population to the insecticide, the rate of application, exogenous weather conditions, and the treatment threshold. Because the economic threshold is a function of the rate of application (see Marra, Gould, and Porter; Higley and Pedigo), the rate of application is assumed to be selected by the farmer prior to the choice of whether or not to make an application. Given the optimal threshold/application rate combination, farmers apply the economic threshold to the observed pest populations to determine whether additional applications are necessary.

The observed number of applications in treatment *i*, N_i, is the number of applications necessary to achieve successful insect control, which results in termination of the applications. Given the series of success probabilities, $\theta_{i1}, \ldots, \theta_{iT}$, where iT is the total number of evaluation points during treatment *i*, the probability of observing $N_i = n$ is

$$\text{(4)} \qquad \text{prob}(N_i = n_i) = \theta_{in} \prod_{b=1}^{n_i-1} (1 - \theta_{ib}).$$

For estimation purposes, this specification is impractical because data on insect populations following each application are not currently available. What *is* available is information about average pest severity during a treatment. Thus, the average probability of success for a treatment can be estimated, but not the individual application success probabilities.

Substituting the average probability of success, $\bar{\theta}_i$, for the success probabilities, $\theta_{i1}, \ldots, \theta_{iT}$, the empirical specification for the probability of observing $N_i = n$ becomes

$$\text{(5)} \qquad \text{prob}(N_i = n_i) = (1 - \bar{\theta}_i)^{n_i - 1}\bar{\theta}_i.$$

Following Mendenhall, Wackerly, and Scheaffer (p. 104), N_i has the form of a geometric random variable, with

$$\text{(6)} \qquad E(N_i) = \frac{1}{\bar{\theta}_i},$$

and

$$\text{(7)} \qquad V(N_i) = \frac{1 - \bar{\theta}_i}{\bar{\theta}_i^2}.$$

The average probability of success during treatment *i*, $\bar{\theta}_i$, is dependent on the average attributes of the insecticides applied, the average rate of application, the severity of the infestation, the type of insect, and the treatment threshold, $\bar{I}_{jt}$:

$$\text{(8)} \qquad \bar{\theta}_i = \left[1 + \exp\left(\beta_1' Z_{im}^{Prod} + \beta_2 A_{im} + \beta_3 S_i + \beta_4 \bar{I}_{jmt} + \sum_{j=1}^{J} \varphi_j D_{ij}\right)\right]^{-1},$$

where Z_i^{Prod} is a vector of average insecticide productive attributes, including target efficacy and persistence; A_i is the average rate applied for treatment *i*; S_i is the severity of infestation during treatment *i*; D_{ij} denotes dummy variables indicating the target insect for treatment *i*; and $\bar{I}_j$ is the treatment threshold for insect *j*. The exponential form of the explanatory variables ensures that $0 \leq \theta \leq 1$. Since $\bar{I}_j$ is not observed, a set of variables representing the right-hand side of (2) is used to proxy for the effects of thresholds. These proxies include average insecticide cost, average insecticide environmental and health attributes, average insecticide efficacy, insect type, insect severity, pest management variables (including use of scouting, beneficial insects, pruning, and pheromones), and price of apples.

Substituting (8) into (5), the probability statement becomes

$$\text{(9)} \qquad \text{prob}(N_i = n_i) = \left\{1 - \left[1 + \exp\left(\beta_1' Z_i^{Prod} + \beta_2 A_i + \beta_3 S_i + \beta_4' I_{ij}^* + \sum_{j=1}^{J} \varphi_j D_{ij}\right)\right]^{-1}\right\}^{n_i - 1} \times \left[1 + \exp\left(\beta_1' Z_i^{Prod} + \beta_2 A_i + \beta_3 S_i + \beta_4' I_{ij}^* + \sum_{j=1}^{J} \varphi_j D_{ij}\right)\right]^{-1},$$

where I_{ij}^* is the vector of treatment threshold proxies. Equation (9) can be simplified to

$$(10)\quad \mathrm{prob}(N_i = n_i) = \left[\exp\left(\beta_1' Z_i^{Prod} + \beta_2 A_i + \beta_3 S_i + \beta_4' I_{ij}^* + \sum_{j=1}^{J} \varphi_j D_{ij}\right)\right]^{n_i - 1} \div \left[1 + \exp\left(\beta_1' Z_i^{Prod} + \beta_2 A_i + \beta_3 S_i + \beta_4' I_{ij}^* + \sum_{j=1}^{J} \varphi_j D_{ij}\right)\right]^{n_i}.$$

The log-likelihood function for this specification of the geometric probability function is

$$(11)\quad \mathrm{LLF} = \sum_{f=1}^{F} \sum_{i=1}^{Y_f} \Bigg\{ (n_{if} - 1) \times \left(\beta_1' Z_{if}^{Prod} + \beta_2 A_{if} + \beta_3 S_{if} + \beta_4' I_{ifj}^* + \sum_{j=1}^{J} \varphi_j D_{ifj}\right) - n_{if} \log\left[1 + \exp\left(\beta_1' Z_{if}^{Prod} + \beta_2 A_{if} + \beta_3 S_{if} + \beta_4' I_{ifj}^* + \sum_{j=1}^{J} \varphi_j D_{ifj}\right)\right]\Bigg\},$$

where F equals the total number of growers in the sample and Y_f is the total seasonal number of treatments for grower f. Parameters of the expected application frequency function will be obtained using the maximum-likelihood routine in TSP. Standard errors are derived from the analytical first derivatives of the likelihood function.

Other economic studies analyzing count data have utilized the Poisson distribution, which describes the number of events occurring within a given time interval (Barmby and Doornik; Hausman, Hall, and Griliches; Lee; Smith, Liu, and Palmquist; Yen and Adamowicz). The geometric distribution is preferred to the Poisson for several reasons. First, the time interval of interest, a treatment, is not of fixed duration. In fact, the length of the interval is defined by the realization of the random variable, such that the interval is bounded by the occurrence of the first and last applications for a given treatment. Comparisons of application frequencies between treatments is thus a comparison of counts from unequal time periods, violating an assumption of the Poisson distribution. Second, the Poisson distribution is characterized by equality of the mean and variance of the distribution. For the sample of treatments by apple growers, the variance of frequency of application is larger than the mean, suggesting that the data are over-dispersed relative to the Poisson distribution. The geometric distribution allows for both under- and over-dispersion in the data. Finally, the Poisson model allows for the occurrence of zeros in the data. In this model, growers always make at least one application given that the treatment threshold has been reached, and thus the application frequency variable is naturally bounded between one and positive infinity. In contrast, the Poisson distribution is bounded between zero and positive infinity. Use of the Poisson model requires arbitrary truncation at zero.

The negative-binomial model has been suggested as a remedy to the problem of overdispersion, but does not allow for under-dispersion and still suffers from the assumption of a fixed time interval (Barmby and Doornik; Hausman, Hall, and Griliches; Lee; Yen and Adamowicz). The truncated Poisson and truncated negative-binomial models have been used to address the zeros problem by truncating the distributions at the zero level (Creel and Loomis; Gomez and Ozuna; Grogger and Carson; Yen and Adamowicz). These arbitrarily truncated distributions are theoretically inferior to the geometric distribution, which is naturally bounded between one and positive infinity. The best candidates for modeling application frequencies are the geometric, zero-truncated Poisson, and zero-truncated negative-binomial models, as all three are bounded between one and positive infinity.

In order to examine the degree of specification error resulting from the assumption that application frequencies follow distributions other than the hypothesized geometric distribution, parameters are estimated using truncated Poisson and truncated negative-binomial distributions. Following Grogger and Carson, the probability distributions and log-likelihood functions for the truncated Poisson and truncated negative-binomial models are as follows:

• Truncated Poisson Model:

$$(12)\quad P(N_i = n_i | N_i > 0) = \frac{\exp(-\lambda_i)\lambda_i^{n_i}}{n_i![1 - \exp(-\lambda_i)]};$$

$$\text{Ln L} = \sum_{f=1}^{F} \sum_{i=1}^{S_f} \{-\lambda_{if} + n_{if}\ln(\lambda_{if}) - \ln(n_{if}!) - \ln[1 + \exp(-\lambda_{if})]\},$$

where

$$\lambda_{if} = \exp\left(\beta_1' Z_i^{Prod} + \beta_2 A_i + \beta_3 S_i + \beta_4' I_{ij}^* + \sum_{j=1}^{J} \varphi_j D_{ij}\right).$$

• Truncated Negative-Binomial Model:

$$(13)\quad P(N_i = n_i | N_i > 0) = \frac{\Gamma\left(\frac{1}{\alpha} + n_i\right)}{\Gamma\left(\frac{1}{\alpha}\right)\Gamma(n_i + 1)} \times \frac{(\alpha\lambda_i)^{n_i}(1 + \alpha\lambda_i)^{-(1/\alpha + n_i)}}{1 - (1 + \alpha\lambda_i)^{-1/\alpha}};$$

$$\text{Ln L} = \sum_{f=1}^{F} \sum_{i=1}^{S_f} \left\{\ln \Gamma\left(\frac{1}{\alpha} + n_i\right) - \ln \Gamma(n_i + 1) - \ln \Gamma\left(\frac{1}{\alpha}\right) + n_i\ln(\alpha) + n_i\ln(\lambda_i) - \left(\frac{1}{\alpha} + n_i\right)\ln(1 + \alpha\lambda_i) - \ln[1 - (1 - \alpha\lambda_i)^{-1/\alpha}]\right\}.$$

The above models will be estimated using the maximum-likelihood procedure in TSP. As with the geometric model, standard errors are derived from the analytical first derivatives of the likelihood function.

Data

Data used to estimate the models consist of survey results from the U.S. Department of Agriculture/National Agricultural Statistics Service (USDA/NASS) "1991 Fruit and Nut Chemical Use Survey." This analysis focuses on insecticide application frequency data for apple growers. Due to limited availability of attributes data, the set of insecticides examined is limited to 22 active ingredients. The active ingredients in this choice subset account for over 90% of insecticide treatments, so limiting the choice set should not result in large specification errors.

The set of data collected on apple growers contains information on active ingredients applied, prices paid for active ingredients, rates of application, dates of applications, intended markets, yields, revenues, and integrated pest management use for 787 growers in seven states. Data on insecticide use were recorded for a randomly selected block of trees from each grower's total production acreage. Recorded applications are thus representative of the grower's insecticide use but do not indicate total use for each grower. Each grower has a sequence of treatments reflecting the number of infestations treated with insecticides during the season. For this analysis, a treatment is defined as consecutive applications for control of a particular target insect. There are a total of 2,427 insecticide treatments for the 787 growers in the sample, or an average of approximately three treatments per grower. Within a given treatment, i, the grower is observed to make N_i applications. This observed number of applications is the dependent variable in this analysis. Application frequency ranges from one (1,061 treatments) to 27 (one treatment), with a mean of 2.61.

Growers apply insecticides to treat a wide variety of insect pests. To reduce the number of parameters in the estimating equations, insects were grouped into 10 categories, based on the 10 most prevalent insect genera/species and an "other" category.[4] Because accurate efficacy information is vital for correct estimation of the model parameters, observations for insecticide applications targeting the "other" category were dropped from the sample. The most frequently treated insect category is moths and maggots (24% of treatments), followed by aphids (20%) and mites (15%).

Variables in the data set are divided into three categories: (*a*) those that differ according to insecticide active ingredient (insecticide attributes), (*b*) those that describe grower economic and production conditions (farm variables), and (*c*) those that describe infestations for a given grower (insect variables). Definitions, means, and standard deviations for variables included in the application frequency models are listed in table 1. The following sections describe these variables and discuss measurement issues.

Definition and Measurement of Insecticide Attributes

For all insecticide attributes, the average attribute level across a treatment is used as the variable. The constructed attribute is a weighted average of the attributes of the insecticides applied by a grower within a given treatment. The constructed attribute is weighted more heavily toward those chemicals applied more times.

Relative effectiveness is difficult to determine due to a lack of consistent laboratory and field tests. Most of the available data from test plot experiments is not comparable across insects or crops. State agricultural extension services often provide relative efficacy rankings based on a four- or five-point scale. Relative efficacy data for western states (Oregon and Washington) were obtained from the pest control manual for Washington state (Washington State University Cooperative Extension). Efficacy data for eastern states (Michigan, New York, North Carolina, Pennsylvania, and Virginia) were obtained from the Virginia/West Virginia Cooperative Extension pest control manual. These two manuals were selected because they contain similar measurement scales and comprehensive information on the full set of insecticides. Efficacy was indicated on a four-point scale, with 4 (excellent control) being the most effective and 1 (poor control) being the least effective.

Realized efficacy of a given application is governed by both the effectiveness of the active ingredient in killing the target insect and the exposure of the target insect population to the active ingredient. Exposure is governed by the initial rate of application, the method of application, and the persistence of the active ingredient. To account for differing levels of potency among active ingredients, rates of application are normalized by the recommended rates of application for the active ingredients. Recommended rates were obtained from the *Crop Protection Chemicals Reference*. The rate variable is thus the proportion of recommended rate applied by the grower. Persistence is governed by the rate of insecticide decay and the solubility of the insecticide. Measures of persistence were obtained from the SCS/ARS/CES Pesticide Properties Database (Wauchope et al.). These measures include the soil half-life and solubility in water.

Insecticide costs are made up of two components: (*a*) explicit materials costs, equal to the price per pound of active ingredient times the rate of application, and (*b*) potential health and environmental costs associated with a given insecticide active ingredient that are not directly observed. Prices per pound of active ingredient were obtained from survey results and from DPRA, Inc. Unobserved health costs are assumed to be correlated with the level of acute oral toxicity to mammals. Toxicity data are in the form of rat lethal oral dosages (LD_{50}s), measured in mg/kg of body weight. Oral LD_{50}s are inversely related to the oral toxicity of an active ingredient. Rat LD_{50}s were taken from *The Pesticide Manual* (Worthing), *The Agrochemicals Handbook*

[4] The "other" category includes apple and thorn skeletonizers, beetles, borers, campyloma bug, citrus blackfly, European apple sawfly, lesser apple worm, lygus bugs, mealybugs, stinkbugs, whitefly, and the survey classification "all other bugs."

Table 1. Summary Statistics for Sample of U.S. Apple Growers

Variable Type and Name	Definition	Mean	Standard Deviation
Application Frequency	Number of applications with an active ingredient for treatment of a target pest.	2.606	2.488
Insecticide Attributes:			
Rate of Application	Average proportion of recommended rate applied.	0.572	0.454
Insecticide Cost	Retail price per lb. of active ingredient × rate of application.	28.091	169.011
Efficacy	Efficacy against target insect on a four-point scale.	3.127	0.823
Solubility (000)	Solubility in water in mg/l.	107.693	255.676
Soil Half-Life	Days to degrade to one-half of initial deposit in average soil type.	24.420	17.939
KoC (000)	Propensity to attach to soil particles.	25.870	124.898
Oral Toxicity	Inverse of rat oral LD_{50}, the amount of active ingredient in mg/kg of body weight necessary to kill one-half of an experimental sample.	0.045	0.054
Farm Variables:			
Fresh Price	Price received for fresh grade apples.	0.187	0.081
Processed Price	Price received for processing grade apples.	0.083	0.033
Aerial Application[a]	Insecticide applied aerially.	0.026	
Alternate Row[a]	Insecticide applied to alternate rows using ground sprayer.	0.178	
Beneficial Insects Used[a]	Grower reported using beneficial insects to control pests.	0.210	
Scouting Used[a]	Grower reported using scouting to determine when to spray.	0.474	
Pruning Used[a]	Grower reported using pruning to control pests.	0.693	
Pheromone Traps Used[a]	Grower reported using pheromone traps for pest control.	0.427	
Average Tree Age	Average age of apple trees in selected block.	15.741	13.155
Applied prior to May[a]	Insecticide applications made in February, March, or April.	0.259	
Applied in May, June, or July[a]	Insecticide applications made in May, June, or July.	0.686	
Applied after July[a]	Insecticide applications made in August, September, or October.	0.054	
Applied in Michigan[a]	Orchard located in Michigan.	0.281	
Applied in New York[a]	Orchard located in New York.	0.141	
Applied in North Carolina[a]	Orchard located in North Carolina.	0.055	
Applied in Oregon[a]	Orchard located in Oregon.	0.126	
Applied in Pennsylvania[a]	Orchard located in Pennsylvania.	0.132	
Applied in Virginia[a]	Orchard located in Virginia.	0.049	
Applied in Washington[a]	Orchard located in Washington.	0.215	
Insect Infestation Variables:			
Target Insect: Aphids[a]	Primary target insect category is aphids.	0.202	

Table 1. (Continued)

Variable Type and Name	Definition	Mean	Standard Deviation
Target Insect: Fruitworms[a]	Primary target insect category is fruitworms.	0.033	
Target Insect: Leafhoppers[a]	Primary target insect category is leafhoppers.	0.083	
Target Insect: Leafminers[a]	Primary target insect category is leafminers.	0.066	
Target Insect: Leafrollers[a]	Primary target insect category is leafrollers.	0.105	
Target Insect: Mites[a]	Primary target insect category is mites.	0.151	
Target Insect: Moths/Maggots[a]	Primary target insect category is moths or maggots.	0.243	
Target Insect: Scales[a]	Primary target insect category is scales.	0.076	
Target Insect: Plum Curculio[a]	Primary target insect category is Plum Curculio.	0.040	
Below Normal Severity[a]	Infestation is of below normal severity.	0.057	
Normal Severity[a]	Infestation is of normal severity.	0.736	
Above Normal Severity[a]	Infestation is of above normal severity.	0.207	

[a] Variable is binary.

(Royal Society of Chemistry), and *The Pesticide Index* (Wiswesser).

Potential costs of ground and surface water contamination are assumed to be correlated with the potential for groundwater leaching and runoff of a given active ingredient. The leaching potential for an active ingredient is governed by the propensity to attach to soil particles (measured by the KoC rating of a chemical) and persistence in soil (measured by the soil half-life). Runoff potential is governed by the solubility of a chemical. Soil half-life, solubility, and KoC measures were obtained from the SCS/ARS/CES Pesticide Properties Database (Wauchope et al.).

Definition and Measurement of Grower Variables

Along with information on insecticide types and quantities, the 1991 USDA/NASS chemical use survey obtained information on economic and production variables including output prices received, tree stock information, method of application, and use of IPM techniques. Both fresh and processed apple prices are included in the model to capture the effects of different marketing outlets. Average age of trees in the selected block is used to capture effects due to both the size of the trees and also potential differences in yield due to tree age. Method of application is measured through the use of indicator variables denoting whether the grower applied insecticides on all rows by ground spray, on alternate rows by ground spray, or aerially. The main IPM techniques of interest are the use of scouting, beneficial insects, pruning, and pheromone traps. Use of each practice is indicated by a zero-one dummy variable equal to one if the grower used the practice and zero otherwise.

The data set contains information on observed application frequencies for apple growers from seven states. To capture some of the differences in climate, precipitation, and production practices across states, dummy variables for states are included in the model specification. The dummy variable corresponding to Michigan is omitted to identify the model. Coefficients on the six remaining state dummies are then normalized with respect to the omitted state.

Definition and Measurement of Infestation Variables

The information variables for each infestation are the primary target insect and the comparative severity of infestation. Target insects were indicated by the growers in their responses to the USDA survey questionnaire.[5] Over 60 separate insect species were identified as target insects. Because incorporation of so many categories would make identification of individual effects difficult, for purposes of this study, insect species were grouped into nine broad categories based on biological similarities.[6]

To identify differences in probabilities of successful management for the nine insect categories, dummy variables corresponding to the nine categories are included in the model specification. The dummy variable corresponding to the aphid category is omitted to identify the model. Coefficients on the remaining eight categories are normalized with respect to aphids.

Initial insect populations are not directly measured. Instead, growers were asked to indicate the relative severity of the infestation. Severity of infestation was indicated by growers on a three-point scale, where 1 denoted that the severity of the infestation was less than the normal severity experienced by the grower, 2 indicated that the severity was normal, and 3 indicated that the severity was worse than that normally experienced by the grower. Thus, severity is relative to what is normal for the individual grower, not relative to regional norms. Dummy variables for severity levels are included in the model specification. The dummy variable corresponding to the normal severity level is omitted to identify the model. Coefficients on the below- and above-normal severity dummies are relative to normal severity infestations.

[5] Farmers were asked to indicate the primary target insect. Farmers treating multiple insects or insect complexes were not asked to list secondary targets.

[6] The nine insect categories are aphids, fruitworms, leafhoppers, leafminers, leafrollers, mites, moths/maggots, scales, and plum curculio.

Estimation of the Application Frequency Model

As noted earlier, the expected application frequency is specified as a function of insecticide attributes, insect type and severity, crop characteristics, pest management practices, and economic and production variables representing the treatment threshold. Expected signs for insecticide attributes can be determined by examining the impact on insect populations. For example, higher average product efficacy is expected to increase the kill rate for a given application. This should increase the average probability of reaching the treatment threshold with a given application, reducing the expected frequency of application.

Some insecticide attributes affect both the cost and the productivity of the insecticide. These dual attributes can have either a greater or a lesser impact on application frequency depending on whether the attributes positively or negatively affect costs and production. For example, soil half-life is a proxy for general persistence of insecticides. As such, a longer soil half-life is expected to increase exposure of insect populations to the insecticide, leading to a higher kill rate for a given application and decreasing the expected application frequency. Soil half-life also contributes to the potential for groundwater leaching, increasing the implicit health costs of the insecticide, increasing the treatment threshold, and decreasing the expected application frequency. As long as an attribute increases or decreases both the productivity and the cost of an insecticide, the signs of the effects will be complementary. This is the case for all of the dual attributes except solubility. Solubility decreases the productivity of an active ingredient by reducing exposure to its insecticidal properties. Solubility increases implicit environmental costs by increasing the potential for runoff into streams and lakes. The productivity effect of solubility would indicate more applications, while the environmental effect would suggest fewer applications. The net effect will have to be determined empirically.

Expected signs for many of the production and economic variables can be determined by

Table 2. Predicted Effects of Variables on the Expected Number of Applications

Attribute Name	Predicted Sign of Effect
Target Efficacy	−
Soil Half-Life	−
Solubility	+/−
KoC	−
Oral Toxicity	−
Insecticide Cost	−
Fresh Grade Price	+
Processed Grade Price	+/−
Crop Age	+
Scouting	−
Use of Beneficial Insects	−
Use of Pruning	−
Use of Pheromones	−
Less Severe Infestation	−
More Severe Infestation	+
Rate of Application	−

examining the latent treatment threshold function. Because the average probability of a given application reducing the target insect population to the treatment threshold is increasing in the threshold level, variables that decrease the treatment threshold will decrease the average probability of successful management, and variables that increase the treatment threshold will increase the average probability. For example, higher prices for fresh apples increase the value of both total output and damage-free output, leading to a lower treatment threshold and a higher expected application frequency. Higher prices for processed apples may increase or decrease application frequencies depending on whether quality effects or output effects dominate.

Variables governing non-insecticide contributions to the effectiveness of a particular application are also included in the estimation. The expected effects of these variables, including crop age, scouting, use of beneficial insects, pruning, use of pheromones, and severity of infestation, are as follows. First, older trees tend to have larger canopies and thus have a greater surface area exposed to possible insect infestation, leading to a higher expected application frequency. Tree age may also be associated with greater yields, thereby increasing potential revenue and lowering the treatment threshold. Scouting and pheromone traps can identify insect types and severities with greater precision, allowing for more accurate applications and leading to decreased expected application frequencies. Use of beneficial insects and pruning can complement insecticide use, decreasing the expected application frequency. Finally, more severe infestations are expected to *increase* the expected application frequency. Table 2 provides a listing of the expected signs of the coefficients of the variables in the application frequency equation.

The marginal effects of insecticide attributes and farm characteristics on the average probability of successful management can be determined by taking derivatives of equation (5) with respect to the variables of interest. The marginal effect of a change in the *k*th ex planatory variable is specified as follows:[7]

$$(14)\quad \frac{\partial \bar{\theta}_i}{\partial k} = -\beta_k \left\{ \exp\left(\beta_1' Z_i^{Prod} + \beta_2 A_i + \beta_3 S_i + \beta_4' I_{ij}^* + \sum_{j=1}^{J} \varphi_j D_{ij} \right) \div \left[1 + \exp\left(\beta_1' Z_i^{Prod} + \beta_2 A_i + \beta_3 S_i + \beta_4' I_{ij}^* + \sum_{j=1}^{J} \varphi_j D_{ij} \right) \right]^2 \right\},$$

or in elasticity form:

$$(15)\quad \epsilon(\bar{\theta}_i, k) = \frac{\partial \hat{\bar{\theta}}_i}{\partial k} \times \frac{k}{\hat{\bar{\theta}}} = -\beta_k k (1 - \hat{\bar{\theta}}_i).$$

The percentage marginal effects of insecticide attributes and farm characteristics on the expected application frequency are equal to the negative of the percentage marginal effects on the average probability of successful management. For nonmarginal changes in binary variables, the percentage change in the average probability of successful management is calculated as

[7] This specification implies that the marginal impacts of pesticide characteristics on the probability of success are the same across insect categories.

Table 3. Estimated Coefficients and Elasticities from Application Frequency Models

	Geometric			Truncated Poisson		Truncated Negative-Binomial	
Variable Name	Estimated Parameter	Asymptotic t-Value	Estimated Elasticity[a]	Estimated Parameter	Asymptotic t-Value	Estimated Parameter	Asymptotic t-Value
Constant	1.229***	6.357		1.431***	13.956	1.280***	6.974
Insecticide Attributes:							
Solubility	0.614-03***	3.762	0.031***	0.378-03***	4.486	0.589-03**	3.822
Soil Half-Life	−0.006***	−2.072	−0.071***	−0.005***	−3.502	−0.006***	−2.148
KoC	0.000	0.837	0.003	0.000	1.358	0.000	0.861
Oral Toxicity	−1.085*	−1.507	−0.022*	−0.264	−0.712	−0.984*	−1.442
Target Efficacy	−0.230***	−5.019	−0.338***	−0.172***	−7.655	−0.224***	−5.195
Insecticide Cost	0.000	0.687	0.001	0.000	1.378	0.000	0.731
Rate of Application	−0.675***	−6.728	−0.182***	−0.500***	−8.642	−0.655***	−6.836
Farm Variables:							
Fresh Grade Price	0.106	0.407	0.001	0.148	1.055	0.111	0.450
Processed Grade Price	0.028	0.047	0.002	0.207	0.638	0.054	0.095
Crop Age	0.004**	1.747	0.028**	0.004***	3.432	0.004**	1.831
Beneficial Insects Used	−0.030	−0.409	−1.645	0.004	0.097	−0.026	−0.386
Scouting Used	0.074	1.189	3.972	0.076***	2.293	0.074	1.259
Pruning Used	−0.073	−1.173	−4.121	−0.069***	−2.080	−0.073	−1.241
Pheromone Traps Used	−0.103*	−1.614	−5.812**	−0.044	−1.263	−0.098*	−1.622
Method of Application:							
Aerial	0.326**	1.898	17.170***	0.257***	3.015	0.314**	1.949
Alternate Row	0.239***	2.872	12.672***	0.214***	5.174	0.234***	2.996
Month of Application:							
May, June, July	−0.122**	−1.692	−7.208**	−0.125***	−3.253	−0.121**	−1.787
August, September, October	−1.192***	−7.019	−69.154***	−1.057***	−8.832	−1.175***	−7.174

Table 3. (Continued)

Variable Name	Geometric: Estimated Parameter	Geometric: Asymptotic *t*-Value	Geometric: Estimated Elasticity[a]	Truncated Poisson: Estimated Parameter	Truncated Poisson: Asymptotic *t*-Value	Truncated Negative-Binomial: Estimated Parameter	Truncated Negative-Binomial: Asymptotic *t*-Value
State Where Applied:							
New York	0.023	0.216	1.127	−0.015	−0.235	0.019	0.190
North Carolina	0.630***	4.862	30.153***	0.436***	6.556	0.607***	4.977
Oregon	0.170*	1.579	8.376**	0.165***	2.772	0.169**	1.655
Pennsylvania	0.528***	5.207	25.518***	0.437***	6.556	0.517***	5.426
Virginia	0.501***	3.626	24.243***	0.390***	5.729	0.456***	3.748
Washington	0.378***	3.743	18.459***	0.290***	5.503	0.370***	3.875
Insect Infestation Variables:							
Target Insect:							
Fruitworms	−0.128	−0.716	−6.951	−0.189**	−1.833	−0.133	−0.785
Leafhoppers	−0.191*	−1.538	−10.370*	−0.239***	−3.369	−0.194**	−1.651
Leafminers	−0.602***	−3.999	−32.333***	−0.568***	−5.934	−0.597***	−4.149
Leafrollers	0.153	1.285	8.216	0.053	0.856	0.143	1.271
Mites	0.025	0.227	1.360	−0.034	−0.593	0.020	0.192
Moths/Apple Maggots	0.867***	7.246	42.735***	0.604***	10.556	0.839***	7.434
Scales	−1.510***	−7.956	−72.716***	−1.432***	−9.722	−1.499***	−8.121
Plum Curculio	−0.364**	−1.971	−19.753**	−0.373***	−3.209	−0.363***	−2.057
Severity of Infestation:							
Less Severe	−0.301***	−2.406	−16.544***	−0.248***	−3.555	−0.293***	−2.468
More Severe	0.172***	2.382	9.300***	0.110***	2.860	0.166***	2.431
Log-Likelihood Function	−3,862.14			−4,250.10		−3,860.13	
X^2 Statistic	28.76			289.49		100.51	
n	2,427			2,427		2,427	

[a] Elasticity of the expected frequency of application with respect to explanatory variable. For binary variable, elasticity is calculated as the percentage change in expected frequency of application when the variable is equal to one.

Single, double, and triple asterisks (*) denote significance at the 15% (two-tailed test), 10%, and 5% level, respectively.

$$(16) \quad \%\Delta = 100 \times \frac{\hat{\theta}_1 - \hat{\theta}_0}{\hat{\theta}_0}.$$

Parameter and elasticity estimates from the geometric application frequency model are presented in table 3, along with nonmarginal percentage effects of changes in scouting, use of beneficial insects, severity, application method, insect type, and state, relative to the omitted levels. Parameter estimates for the truncated Poisson and truncated negative-binomial models are also presented in table 3.

Goodness of fit is tested using a Pearson type goodness-of-fit statistic calculated as follows (Mendenhall, Wackerly, and Scheaffer, p. 647):

$$(17) \quad X^2 = \sum_{i}^{k} \frac{[q_i - \hat{E}(q_i)]^2}{\hat{E}(q_i)},$$

where q_i is the cell frequency for $N = i$, $i = 1, \ldots, k$, where k is the highest observed number of applications; and $\hat{E}(q_i) = \hat{p}_i FS$, where $\hat{p}_i$ is the probability that $N = i$ estimated from the model, and FS is the total number of treatments. X^2 has approximately a χ^2 distribution with $(k - 2)$ degrees of freedom. Large values of X^2 will indicate a poor fit between the predicted distribution of application frequencies and the observed distribution. The X^2 statistic is lowest for the geometric model, at 28.8, and is under the 5% critical value ($k = 27$) of 37.7, indicating the geometric distribution is a good match for the observed distribution. The X^2 statistic values indicate that the geometric model is superior to both the truncated Poisson and negative-binomial models.

Results

Results show a relatively low average success rate for apple growers using insecticides to control insect populations. The estimated parameters are inversely related to the average probability of successful management. The mean estimated average probability of successful management is 0.38, although the estimated average probability of successful management varies considerably from state to state and for growers treating different insect categories. Table 4 provides a listing of the percentage differences in the average probability of successful management for the seven apple producing states in the sample. The percentage differences in the average probability of successful management for the nine insect categories treated in the sample are presented in table 5.

The average probability of successful management for North Carolina, Pennsylvania, and Virginia is significantly lower (by 14% to 30%) than for most other apple producing states. The largest difference in the average probability of successful management is between North Carolina and Michigan, where a Michigan grower has, on average, a 43.2% higher average probability of successful management than a North Carolina grower. The overall results seem to indicate that pesticide applications are the most effective in the northeast (Michigan and New York), followed by the northwest (Oregon and Washington) and the mid-Atlantic states (North Carolina, Pennsylvania, and Virginia). This may reflect the warmer, more humid conditions in the mid-Atlantic region which can lead to increased insect pressure.

The estimated difference in average probability of successful management between growers treating scales and growers treating other insect categories is the most pronounced. The average probability of successful management of scales is significantly higher (by 31% to 201%) than for any other insect category. Moths are the most difficult insect category to control, with significantly lower probabilities of successful management (by 38% to 67%) than any other insect category.

The results from the parameter estimation suggest that the expected application frequency is significantly decreasing in the rate of application, efficacy, half-life, oral toxicity, and use of pheromone traps, and is significantly increasing in solubility, crop age, severity of infestation, and use of aerial and alternate row application methods. All of the significant parameters have signs in agreement with theoretical expectations. The marginal effect of solubility on the expected application frequency is positive, indicating that potential losses

Table 4. Percentage Difference in Probability of Successful Management for the Seven Major Apple Producing States

	To						
From	MI	NY	NC	OR	PA	VA	WA
Michigan		−1.13	−30.15***	−8.38*	−25.52***	−24.24***	−18.46***
New York	1.15		−29.36	−7.33	−24.67***	−23.38***	−17.53***
North Carolina	43.17***	41.56***		31.18***	6.64	8.46	16.74*
Oregon	9.14*	7.91	−23.77***		−18.71***	−17.32***	−11.00***
Pennsylvania	34.26***	32.75***	−6.22	23.02***		1.71	9.48
Virginia	32.00***	30.51***	−7.80	20.95**	−1.68		7.64
Washington	22.64***	21.26***	−14.34**	12.37**	−8.66	−7.09	

Notes: Differences are evaluated at the means of the explanatory variables. Single, double, and triple asterisks (*) denote significance at the 15% (two-tailed test), 10%, and 5% level, respectively.

Table 5. Percentage Difference in Probability of Successful Management for the Nine Major Insect Categories

	To								
From	Aphids	Fruitworms	Leafhoppers	Leafminers	Leafrollers	Mites	Moths/ Maggots	Scales	Plum Curculio
Aphids		6.95	10.37*	32.33***	−8.22	−1.36	−42.74***	72.72***	19.75**
Fruitworms	−6.50		3.20	23.73***	−14.18**	−7.77	−46.46***	61.49***	11.97
Leafhoppers	−9.40**	−3.10		19.90***	−16.84***	−10.63*	−48.42***	56.49***	8.50
Leafminers	−24.43***	−19.18***	−16.60***		−30.64***	−25.46***	−56.73***	30.52***	−9.51
Leafrollers	8.95	16.53*	20.25***	44.18***		7.47	−37.61***	88.18***	30.47***
Mites	1.38	8.43	11.89*	34.16***	−6.95		−41.95***	75.10***	21.40**
Moths/Maggots	74.63***	86.77***	92.74***	131.09***	60.28***	76.25***		201.61***	109.12***
Scales	−42.10***	−38.08***	−36.10***	−23.38***	−46.86***	−42.89***	−66.84***		−30.67***
Plum Curculio	−16.50***	−10.69	−7.84	10.51	−23.36***	−17.63***	−52.18***	44.23***	

Notes: Differences are evaluated at the means of the explanatory variables. Single, double, and triple asterisks (*) denote significance at the 15% (two-tailed test), 10%, and 5% level, respectively.

in productivity outweigh potential impacts of runoff contamination. The remaining continuous explanatory variables are insignificant in explaining variation in application frequencies. Of the four insignificant parameters with definite sign predictions, two—fresh and processed apple prices—have signs that agree with expectations, and two—insecticide cost and KoC—have signs opposite of expectations. The insignificance of insecticide cost suggests that input prices have little impact on treatment thresholds, and subsequently have little impact on the expected number of applications. This tends to corroborate findings in the pesticide demand literature that growers are unresponsive to pesticide prices (Fernandez-Cornejo; Miranowski; Carlson).

The estimated elasticity for the rate of application is −0.18. This indicates that the rate of substitution between rates of application and expected numbers of applications is relatively low. Increasing the proportion of the recommended rate applied thus provides little benefit to the grower in terms of reducing the expected number of applications.

Efficacy is highly significant in explaining application frequency. Increasing the average effectiveness of an application from fair to good and from good to excellent decreases the expected application frequency by 14% and 13%, respectively. This suggests that product choice is essential in reducing the number of insecticide applications.

As expected, month of application and method of application have significant impacts on the expected application frequency. The expected application frequency is, on average, 17% higher for growers applying insecticides aerially than for those applying on the ground to all rows. Growers applying on the ground to alternate rows have an average expected application frequency 13% higher than growers applying to all rows.

The expected application frequency decreases as growers move from early season to mid- and late season treatments. The expected application frequency for mid-season treatments is 8% lower than for early season applications. The expected application frequency for late season treatments is 70% lower than for early season applications. Reduced numbers of applications toward the end of the season may reflect regulatory constraints, primarily pre-harvest intervals and residue tolerances.

Finally, the severity of the infestation faced by the grower significantly increases the expected application frequency. A less severe than normal infestation leads to a reduction in the expected application frequency of 17%, while a more severe infestation leads to a 9% increase in the expected application frequency.

Conclusions

This analysis has shown that the observed frequency of insecticide applications can be modeled as a geometric random variable. It is demonstrated that the geometric distribution of application frequencies is theoretically consistent with growers' use of treatment thresholds and empirically superior to both the truncated Poisson and truncated negative-binomial models. The resulting parameter estimates will be useful to policy makers in designing policies to reduce total pesticide use. The estimated relationships between IPM practices and application frequencies indicate that the type of IPM practice adopted by the farmer matters, as pheromone traps were the only practice to actually decrease application frequencies.

The geometric model can be applied easily to other crops to identify significant factors leading to increased insecticide applications. Pesticide use information is available from the USDA for several crops, making data acquisition relatively easy and inexpensive. The model may therefore be useful in analyzing the comparative effectiveness of IPM and other government-backed programs in reducing pesticide use across crops.

Parameter estimates reveal that most of the variation in the average probability of success in controlling insects with a particular application is due to differences in insecticide efficacy, exposure to insecticide materials, target insect, region, and severity of infestation. Variables influencing the treatment threshold have little impact on the average probability of successful management, with the exception of insecticide toxicological attributes. This may be due to a low degree of variation in treatment thresholds in the sample or to low correlation between the observed proxies and the actual treatment threshold.

High insecticide toxicity does increase the acceptable level of damage, resulting in reduced application frequencies, but the effect is relatively small, with an elasticity of only −0.02. Successful management of insect pests also depends on the method of application, with ground application to all rows being the most effective. This is supported by the fact that the majority of treatments (79.7%) use ground application to all rows. Insecticide use may be further reduced by encouraging less use of aerial sprays. This may also have additional positive public health impacts by reducing poisonings due to aerial drift.

Future analyses of application frequencies would benefit from improved data on treatment thresholds for the set of target insects. If such data were available, it would not be necessary to assume an arbitrary functional form relating economic variables and the unobservable treatment threshold. This would allow for direct estimation of the relationship between desired levels of control and the average probability of successful management. Likewise, improved data on insecticide efficacy in each region would improve the model, allowing some of the variation captured by the state dummy variables to be captured by the differences in efficacy in the states. Finally, detailed data on timing of applications, weather conditions at the time of application, and reductions in insect populations after each application would allow for a more complete specification of the probability of successful management, improving both the fit of the model and our understanding of the determinants of application frequency.

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