Intensity of Integrated Pest Management (IPM) Practices Adoption by U.S. Nursery Crop Producers

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Abstract

We examined the intensity of integrated pest management (IPM) techniques adoption by U.S. nursery crop producers using parametric and nonparametric methods. We used data collected from 2009 National Nursery Survey to identify effects of variables associated with nursery producers on the number of IPM techniques used. Our results indicated that Pacific and Southeast regions, sales of trees, year farm was established, and number of trade shows were positively related to the number of IPM techniques adopted, whereas sale volume of trees/shrubs and foliage had opposite effects. We found a nonparametric specification superior compared to a parametric specification in IPM intensity analysis.

Key words: IPM, Negative Binomial, Nonparametric, Plant Nursery, Quasi Likelihood, Zero Inflated Negative Binomial

JEL Classifications: M31, L14

Intensity of Integrated Pest Management (IPM) Practices Adoption by U.S. Nursery Crop Producers

Pest management is one of the most important decision components from the perspective of cost and time involved in nursery crop production in the United States. Due to negative effects of chemical application on human and environmental health, difficulty of finding right types of chemicals given pest incidence and pest resistance, and increased regulations regarding environmental impacts, integrated pest management (IPM) has been used as an alternative pest management approach in plant nursery production. The National Coalition on IPM (1994) defines IPM as ‘a sustainable approach to managing pests by combining biological, cultural, physical, and chemical tools in a way that minimizes economic, health and environmental risks. Since the inception of IPM in 1972, it has been combining various control methods in pest suppressant technologies such as biological control, cultural control, mechanical and physical control, chemical control, host plant resistance and regulatory control. Regions with higher overall pest pressure due to warm and humid conditions, particularly the Southeast U.S., are more amenable to IPM adoption (Sellmer et al., 2004). This area also happens to have the highest number of plant nursery operations in the U.S.

Nursery producers benefit from adopting IPM as they can achieve acceptable control using fewer pesticides. Although IPM might be costly at the beginning, nursery producers will benefit from IPM adoption in a long run. At the beginning, nursery growers need to invest time to learn different pest and related information; however compensation from cost savings from adoption of IPM translates to better plant and environmental qualities. There are ample evidences of producers being able to save chemical expenses from IPM use (Adkins et al. (2012)) .

There exists a plethora of studies (example includes (Fernandez-Cornejo and Ferraioli, 1999; Rejesus et al., 2009; Sharma et al., 2011)) on IPM technology adoption in agriculture, but few deal with IPM adoption in nursery production. Intensity of technology adoption has been studied in other crops and livestock using count data model techniques (Mishra and Park, 2005; Paxton et al., 2011; Rahelizatovo and Gillespie, 2004). Nursery producers may adopt multiple IPM methods once they have positive experience and feel comfortable with the technology. To understand the adoption intensity of multiple IPM techniques by plant nursery producers, we used count data models. We utilized a combination of parametric and nonparametric methods to calculate the effects of several pertinent variables on the intensity of IPM adoption by plant nursery producers.

1. Method

Poisson models are a common choice to analyze count data under equi-dispersion (equal mean and variance) assumption. Unobserved heterogeneity and concerns regarding the prediction of probability of zero counts make a Poisson model less attractive in empirical estimation (Cameron and Trivedi, 2010) . When an assumption of equi-dispersion is rejected, a negative binomial model is used. A dispersion parameter in a negative binomial model addresses heterogeneity present in the model but it is difficult to identify a true value for the dispersion parameter. For example, Park and Lord (2008) make adjustment in the maximum likelihood method that minimize or correct bias due to small sample size and low sample mean. They developed a relationship between true and estimated dispersion parameters that reduces bias of estimated parameters. Cadigan and Tobin (2010) used strata based negative binomial distribution to make adjustment in dispersion parameters in their study.

There exists an alternative way to address heterogeneity in a count data model. Staub and Winkelmann (2012) claim that zero-inflated maximum likelihood estimates have both consistent and efficiency problems so they proposed an alternative Poisson quasi-likelihood estimator (PQL). Zhou et al. (2012) proposed a log-normal based negative binomial distribution. Additionally, some researchers such as Sharma et al. (2011) used nonparametric (NP) count data models to study number of technology adoption and pest control strategies among UK cereal farmers. They found that nonparametric model specification is preferred to parametric model. Based on the summary of existing literature presented, we used both parametric and nonparametric methods to study effects of different variables on the number of IPM practices adopted.

1.1 Parametric method

The Poisson model specification is given as

$$\Pr(y = y) = \frac{e^{-\mu}\mu^{y}}{y!}, y = 0,1,2, \ldots, \text{n.} \tag{1}$$

Here, y represents number of IPM adoption by a plant nursery producer. Count data is always positive so the usual parameterization for mean in the Poisson model is $\mu = \exp(x'\beta)$, such that $\mu > 0$.

Unobserved heterogeneity which causes additional variability in the variable of interest can be generated by adding multiplicative randomness, such that parameterization for mean is $\mu\nu$, where ν is random variable. A well-known distribution used in econometrics literature for random variable ν is the gamma distribution, so $\nu \sim \text{Gamma}\ (1, \alpha)$ where α is the variance parameter of the gamma distribution. Then the marginal distribution of y is the Poisson-gamma mixture with a closed form, which is the negative binomial distribution with parameter (μ, α) with the following probability mass function

$$\Pr(y = y|\mu, \alpha) = \frac{\Gamma(\alpha^{-1}+y)}{\Gamma(\alpha^{-1})\Gamma(y+1)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\mu+\alpha^{-1}}\right)^{y} \quad (2)$$

where $\Gamma(.)$ denotes the gamma integral. The mean and variance of these probability mass functions are μ and $\mu(1 + \alpha\mu)$.

Zero inflated model

As mentioned earlier in this section, another problem of the Poisson model is underestimation of number of zeros in the sample data. An alternative is a hurdle model that relaxes the assumption that zeros and the positives come from the same data generating process. According to Cameron and Trivedi (2005) and Cameron and Trivedi (2010), zeros are determined by the density $f_1(.)$, so that $\Pr(y = 0) = f_1(0)$ and $\Pr(y > 0) = 1 - f_1(0)$. The positive count comes from the truncated density $f_2(y|y > 0) = (1 - f_2(0))$, which is multiplied by $\Pr(y > 0)$ to ensure that probabilities sum to 1. This is a two stage model specification, each being a model of one decision. Zero inflated negative binomial distribution is maximum likelihood estimation; however, Staub and Winkelmann (2012) find that Poisson quasi likelihood (PQL) estimator is robust to misspecification as it estimates the regression parameter consistently regardless of the true distribution of the counts. The Poisson quasi likelihood can be presented as

$$ql(\beta, \delta) = \sum_{i}^{n} y_i \ln\, \tilde{\lambda}(x_i, z_i, \beta, \delta) - \tilde{\lambda}(x_i, z_i, \beta, \delta) \quad (3)$$

where $\tilde{\lambda}(x_i, z_i, \beta, \delta) = \exp(x_i\beta)/(1 + \exp(z_i\delta))$.

Test of over-dispersion

Cameron and Trivedi (2005) suggest a formal test of equi-dispersion after running a Poisson regression. Let us consider over dispersion to be of the following form $V[y_i|x_i] = \mu_i + \alpha\mu_i^2$ with α as an unknown parameter. Then over-dispersion test statistics for $H_0{:}\,\alpha = 0$ versus $H_1{:}\,\alpha > 0$ is computed by estimating a Poisson model, constructing fitted values $\hat{\mu}_i = \exp(x_i'\hat{\beta})$, and running the auxiliary OLS regression (without constant)

$$\frac{(y_i-\hat{\mu}_i)^2-y_i}{\hat{\mu}_i} = \alpha\mu_i + u_i. \tag{4}$$

Here, u_i is an error term. According to Cameron and Trivedi (2005), the reported t-statistics for α are asymptotically normal under the null hypothesis of no over dispersion. An alternative way for test of over dispersion is the likelihood ratio test with negative binomial model as full model and Poisson model as restricted model. Significance of the likelihood ratio test implies the presence of over dispersion in the sample.

Marginal effects

We use marginal effect for interpretation of coefficients. Dfferentiations of conditional mean of equation 2 yields

$$\frac{\partial E[y|X]}{\partial x_j} = \beta_j \exp(X'\beta). \tag{3}$$

Here, the scalar x_j denotes the j^{th} regressor. For purposes of reporting a single response value, we used average marginal effects given by the following expression

$$N^{-1}\sum_i \frac{\partial E[y_i|X_i]}{\partial x_{ij}} = \hat{\beta}_j \times N^{-1}\sum_i \exp(\hat{X}_i'\ \hat{\beta}). \tag{4}$$

1.2 Nonparametric method

Use of a generalized kernel estimation in a nonparametric method allows incorporation of both continuous and categorical variables (Racine and Li (2004). We consider a nonparametric model with both continuous (X) and categorical (Z) explanatory variables

$$Y_i = g(X_i, Z_i) + u_i \tag{5}$$

where $g(.)$ has an unknown functional form. We also assume that $u_i$has mean zero and variance$Var(u_i|x_i) = \sigma^2(x_i)$. Suppose that $w(.)$ represents a univariate kernel function so that we can write the product kernel as

$$W\left(\frac{x_i - x}{h}\right) = \prod_{j=1}^{J} w\left(\frac{x_{ji} - x_j}{h_j}\right) \tag{6}$$

where x_{ji} and x_j are j^{th} elements of x_i and x, and h_j represents the smoothing parameter for all the continuous variable. We used standard normal kernel function as our kernel type, expressed as

$$w(v) = \frac{1}{\sqrt{2\pi}} e^{\frac{v^2}{2}} \quad . \tag{7}$$

The kernel function for discrete variable is expressed as

$$l(z_{ji}, z_j, \lambda_j) = \begin{cases} 1 \; if \; z_{ji} = z_j \\ \lambda \; if \; z_{ji} \neq z_j \end{cases} \tag{8}$$

where z_{ji} and z_j are j^{th} elements ($j = 1$ to J), λ_j is the smoothing parameter which lies in the interval [0,1]. This indicates that the kernel function becomes indicator function when $\lambda_j = 0$, whereas the kernel function is a constant for all values of the discrete variables when $\lambda = 1$. Then according to Racine and Li (2004) the product kernel for discrete variable is expressed as

$$L(z_i, z, \lambda) = \prod_{j=1}^{J} l\left(z_{ji}, z_j, \lambda_j\right). \quad (9)$$

Using equations 8 and 11, we employ a local linear kernel estimator to estimate $h\left(x_{i,z_i}\right)$. Using Racine and Li (2004), the local linear method is estimated using minimization of following expression

$$\min_{(\alpha,\beta)} \sum_{i=1}^{n} (p_i - \alpha - (x_i - x)'\beta)^2 W(x_i, x, h) \times L(z_i, z, \lambda) \quad (10)$$

where $\hat{h}(x, z) = \hat{\alpha}$ and $\hat{\beta}(x, z) = \hat{\beta}$ denote the local linear estimates of the conditional mean and the derivative at the point (x, z), respectively. Choice of smoothing parameter (h, λ) is important in a nonparametric estimation method. We select appropriate bandwidths for categorical and continuous variables by employing the expected Kullback-Leibler Cross Validation Method (Hurvich et al., 1998) which is more efficient than other approaches.

2. Data

Data for this analysis were obtained from National Nursery Survey, 2009[1]. Data about sales, employment, product types and forms, market channels, production and marketing practices, regional trade, and other influencing factors were collected for the year 2008 using mail and e-mail surveys in 50 U.S. states. A list of nursery producers for all states was taken from sources that included National Plant Health Board, state departments of agriculture, grower associations and business databases. Dillman (2000) survey protocol was used to design and implement the

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[1] The 2009 National Nursery Survey was conducted by the Green Industry Research Consortium of University Horticulturists and Economists, organized as a multi-state project (S-1021) under U.S. Department of Agriculture, National Institute of Food and Agriculture.

survey, which was sent to 15,000 producers whereas email survey was sent to 1,900 producers in 12 states. A total of 3,044 valid responses were received with a 17% response rate. Out of these samples 312 were obtained from e-mail survey.

The survey listed 22 different IPM techniques were adopted by nursery producers. Details on specific technique and number of producers adopting these techniques are given in Table 1. Use of techniques such as removing infested plants, hand weeding, inspecting incoming stock was adopted by large percentage of nursery producers. Percentage of farmers adopting each technique is provided in Figure 1, where 11% did not adopt any techniques. Most of the nursery producers adopted four to ten IPM techniques. Pair-wise correlation coefficients for all IPM techniques show that only a few practices were jointly adopted. For example, spot treatment with pesticides was correlated with remove infested plants, alternate pesticides to avoid chemical resistance, elevate or space plants for air circulation, and disinfect bench/ground cover. Further, use cultivation- hand weeding was correlated with remove infested plants. However, these correlation coefficients were close to 0.5 and only for a few IPM practices, so it is safe to analyze data using count models.

Our dependent variable is the number of IPM techniques adopted by nursery growers. The number of IPM techniques available to nursery producers ranged from 0 to 22. Explanatory variables were regional dummies (Northeast, Midwest, Pacific, Southeast), and sales of plant group (trees/shrubs, bedding plants, vines, foliage and other), contracted production (total sales under contract, contract to other producers, to garden centers and to mass merchandiser), age, computer management aids, channel diversity etc. Choice of these explanatory variables is consistent with the study by Hinson et al. (2012). Explanatory variables and summary statistics are provided in Table 2.

3. Results and Discussion

Parametric results of negative binomial, zero inflated negative binomial and PQL are provided in Table 3 and corresponding model marginal effects are given in Table 4. We first tested for model specification to interpret results obtained from these models. The coefficient of alpha parameter was significant leading, to a decisive rejection of the null of equi-dispersion ($\alpha = 0$). Consistent with this, there was a large increase in the log-likelihood from -5930.43 to -5564.93 at the cost of one additional parameter α than the Poisson model. The highly significant LR test statistics (731.37) indicated considerable improvement in the fit of the model. Figure 1 shows there were many zeros, a potential problem as an NB model does not capture excess zeros. Hence, we also tested the zero inflated model using the LR test of Vuong (1989) to identify a better model between negative binomial and zero inflated negative binomial (ZINB) models. A large positive test value favors a ZINB model whereas a large negative value favors an NB model (Cameron and Trivedi, 2010). In our case, the test statistics was 3.01 and one-sided p-value of this test statistics was 0.002, favoring the ZINB model. Staub and Winkelmann (2012) found that PQL model was consistent compared to ZINB model, so our interpretation of results based on PQL model is presented in following paragraphs. Parameter significance was measured at a 10% level.

Results suggest those nursery growers located in Pacific and Southeast regions adopted more IPM methods compared to others. Marginal effects indicated that nursery growers in the Pacific region adopted 0.1 more practices compared to farmers in other regions, and nursery growers in the Southeast region adopted 0.073 more practices compared to other regions. An increase in sales of trees/shrubs (*pg1*) led to lower IPM adoption. These products tend to be less affected with pests and diseases. We found similar effects for sale of foliage (*pg4)*, but increase in sales of vines (*pg3*) and other plants (*pg5*) increased the number of practices adopted.

We found that if production is contracted to other producers (*tcop*), IPM techniques adopted increased. Marginal effect for this variable is 0.147 which indicates that IPM adoption is 0.147 higher among those producers who contracted to other producers. We found similar results for contract to garden center (*tcgc*) and the number of IPM practices increased by 0.092. We also found that number of trade shows attended in 2008 (*trade*) has a positive effect of 0.007 on number of IPM techniques. Further, an increase in expenses on trade shows (*patss*) had a positive effect on number of IMP technique adoption. We found that increase in farm age increased the number of practices by 0.002. With respect to use of the computer as a management aid (*dcomp*), the number of practices used increased by 0.304.

Nonparametric results

We used local-linear least squares cross-validation bandwidth selection method (Racine and Li, 2004)[2] to estimate a nonparametric model. The R^2 value for a nonparametric model is 0.37 which is very high compared to parametric results. Therefore, in terms of model fit, a nonparametric model performs better than the parametric models estimated. The cross validation estimates, the associated scale factors and the P-values for our nonparametric regression are presented in Table 5. These p-values are generated by employing and an iid bootstrap process. The significance test is equivalent to a t-test for our parametric models. Table 5 shows that regions, sales of bedding plants, vines, foliage and others, sales under contract, contract to other producers, contract to mass merchandisers, number of trade shows and age of farm established are all statistically significant. Figure 2 shows our results as a set of partial plots. The plot shows

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[2] All programming was done using R 2.15.0 and package np (see www.r.project.org; R, 2012).

relation between each explanatory variable against number of IPM techniques, assuming that all other independent variables take their mean values. Nonparametric estimate with point-wise confidence interval and bootstrap error are used to plot confidence interval.

We observed that regions are statistically significant where the labels indicate Midwest (1), Northeast (2), Pacific (3) and Southeast (4). We can see that as sales of bedding plants (*pg2*) increased, the number of practices adopted also increased; however, it decreases when sales volume reached $100 million. We found that number of IPM practices decreased as sales of vines (*pg3*), foliage (*pg4*) and other (*pg5*) increased. We found that nursery producers with contract to other producers (*tcop*) and contract to mass merchandisers (*tcmm*) adopt more IPM techniques. As total sales under contract (*ctcts*) increased the number of IPM adoption decreased. We found that trade had a mixed effect on number of IPM practices - as number of trade shows increased up around 20, the number of IPM adopted also increased and then decreases and likely to remain constant. Our results also show that as age of the business increased (*agef*), the number of IPM techniques adopted decreased. Finally, nursery producers who used computer as a management aid (*dcomp*) had a higher number of IPM techniques adopted than those who do not.

4. Conclusions

We examined the issue of IPM adoption, and our focus has been on the intensity of IPM adoption rather than whether or not a specific IPM technology has been adopted by plant nursery producers. By using 2009 National Nursery Survey data, we identified different factors on the intensity of adoption of IPM practices to manage pests. We used better parametric model PQL which is more consistent than ZINB. We found that nonparametric model is preferred over parametric method. We employed cross-validation method and we were able to combine categorical and continuous variables thereby avoiding a sample splitting problem. Although nonparametric model is computationally intensive, we utilized it as it does not require a prior functional form specification.

Overall, results from the parametric model indicated that Pacific and Southeast region, sales of trees, farm age, number of trade shows have positive relation to the number of IPM adopted, whereas sales of trees/ shrubs and foliage had opposite effects. Overall, our nonparametric model gave slightly different results for some explanatory variables that are statistically significant compared to the parametric models. In particular, the nonparametric model indicated total sales under contract (*ctcts*) and contracts to mass merchandiser (*tcmm*) as important variables in determining the number of IPM practices adopted, but these were not significant in the parametric model. Contrasting results were found for some variables, namely sales of vines (*pg3*) and firm age (*agef*) between parametric and nonparametric results.

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Table 1: IPM technology and percentage of nursery producers adopting the technology

IPM Technology	Percentage of Nursery Producers Adopting the Technology
Remove infested plants	69
Alternate pesticides to avoid chemical resistance	46
Elevate or space plants for air circulation	47
Use cultivation, hand weeding	64
Disinfect benches/ground cover	35
Use sanitized water foot baths	4
Soil solarization/sterilization	12
Monitor pest populations with tarp or sticky boards	25
Adjust pesticide application to protect beneficial	30
Use mulches to suppress weeds	37
Beneficial insect identification	34
Inspect incoming stock	57
Manage irrigation to reduce pests	43
Spot treatment with pesticides	58
Ventilate greenhouses	36
Use of beneficial insects	22
Keep pest activity records	19
Adjust fertilization rates	32
Use screening/barriers to exclude pests	12
Use bio pesticides/ lower toxicity	25
Treat retention pond water	4
Use pest resistant varieties	30

Table 2: Variable definition and descriptive statistics

Varible Names	Variable Definition	Mean	SD
Regions			
Midwest	Equals 1 if Midwest, otherwise 0	0.16045	0.37
Northeast	Equals 1 if Northeast, otherwise 0	0.21438	0.41
Pacific	Equals 1 if Pacific, otherwise 0	0.14281	0.34
Southeast	Equals 1 if Southeast, otherwise 0	0.25034	0.43
Others	Equals 1 if region is other than Midwest, Northeast, Pacific and Southeast, otherwise 0	0.23100	0.42
Plant Group			
pg1	Total sales of trees/shrubs ($100,000)	34.4819	42.92
pg2	Total sales of bedding plants ($100,000)	11.5796	26.24
pg3	Total sales of vines ($100,000)	11.5252	23.37
pg4	Total sales of foliage ($100,000)	3.84525	16.89
pg5	Total sales of other plants ($100,000)	36.3852	39.87
Contracted production			
Tcop	Contract to other producers (1 if positive, otherwise 0)	0.07191	0.25
Ctcts	Total sales under contract ($100,000)	8.71382	22.49
Tcgc	Contract to garden centers (1 if positive, otherwise 0)	0.04986	0.21
Tcmm	Contract to mass merchandisers (1 if positive, otherwise 0)	0.02171	0.14
Kinds of promotions			
Trade	Number of trade shows attended in 2008	1.20692	3.95
Pawsss	Website promotion expenses ($000)	7.84912	21.05
Patss	Trade show promotion expenses ($000)	6.38865	19.14
Others			
Agef	Firm age (2008 minus year established)	22.8276	20.27
Psns	Share of negotiated sales (standard terms such as price were changed)	30.6355	34.10
Dcomp	Computer management aids (1 if used >3 functions from a list of 11, otherwise 0)	0.57938	0.49

Table 3. Parametric regression results

	Negative Binomial		Zero Inflated Negative Binomial		Poisson Quasi Likelihood	
Variables	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	1.696	**0.00**	1.761	**0.00**	1.981	**0.00**
Midwest	-0.013	0.75	-0.016	0.69	-0.012	0.75
Northeast	0.006	0.86	0.008	0.82	0.007	0.84
Pacific	0.085	**0.03**	0.081	**0.04**	0.100	**0.01**
Southeast	0.055	0.12	0.049	0.16	0.073	**0.03**
pg1	-0.001	**0.05**	-0.001	**0.01**	-0.005	**0.00**
pg2	0.004	**0.00**	0.003	**0.00**	-0.001	0.67
pg3	0.000	0.60	0.000	0.62	0.009	**0.01**
pg4	0.001	**0.04**	0.001	**0.06**	-0.002	**0.10**
pg5	0.000	0.48	-0.001	0.16	0.003	**0.05**
Tcop	0.138	**0.00**	0.137	**0.00**	0.147	**0.00**
Ctcts	0.000	0.37	0.001	0.25	0.001	0.24
Tcgc	0.087	**0.06**	0.082	**0.07**	0.092	**0.04**
Tcmm	0.052	0.41	0.056	0.34	0.071	0.22
Trade	0.012	**0.06**	0.011	**0.06**	0.007	**0.03**
pawsss	0.001	0.33	0.000	0.44	0.001	0.27
Patss	0.002	**0.00**	0.001	**0.01**	0.002	**0.00**
Agef	0.002	**0.00**	0.003	**0.00**	0.002	**0.00**
Psns	0.000	0.59	0.000	0.61	0.000	0.24
dcomp	0.322	**0.00**	0.304	**0.00**	0.304	**0.00**
ln alpha	-1.822		-2.0188			
Pseudo R2	0.029					
LL	-5564.930		-5536.509		-5824.839	

Note: Over dispersion test coefficient is 0.124 with p-value equal to 0.00.

Likelihood ratio (LR) test for over-dispersion is 731.37 with p-value equal to 0.00

Vuong test of ZINB vs. standard negative binomial: z = 3.01 Pr > z = 0.00

Table 4. Marginal effects from parametric regression

	Negative Binomial		Zero Inflated Negative Binomial		Poisson Quasi Likelihood	
Variables	Estimate	P-value	Estimate	P-value	Estimate	P-value
Midwest	-0.102	0.75	-0.127	0.68	-0.012	0.75
Northeast	0.051	0.86	0.067	0.82	0.007	0.84
Pacific	0.697	**0.04**	0.661	**0.04**	0.100	**0.01**
Southeast	0.444	0.12	0.392	0.17	0.073	**0.03**
pg1	-0.009	**0.05**	-0.010	**0.04**	-0.005	**0.00**
pg2	0.030	**0.00**	0.028	**0.00**	-0.001	0.67
pg3	-0.003	0.60	-0.001	0.96	0.009	**0.01**
pg4	0.012	**0.04**	0.012	**0.04**	-0.002	**0.10**
pg5	-0.003	0.48	-0.004	0.36	0.003	**0.05**
tcop	1.167	**0.00**	1.150	**0.00**	0.147	**0.00**
ctcts	0.004	0.37	0.005	0.25	0.001	0.24
tcgc	0.720	**0.08**	0.681	**0.08**	0.092	**0.04**
tcmm	0.423	0.42	0.462	0.36	0.071	0.22
trade	0.093	**0.06**	0.088	**0.06**	0.007	**0.03**
pawsss	0.004	0.33	0.003	0.44	0.001	0.27
patss	0.013	**0.00**	0.012	**0.01**	0.002	**0.00**
agef	0.020	**0.00**	0.022	**0.00**	0.002	**0.00**
psns	0.002	0.59	0.002	0.61	0.000	0.24
dcomp	2.400	**0.00**	2.273	**0.00**	0.304	**0.00**

Table 5. Nonparametric regression results

	Cross Validation Values	Scale factor	P-values
regions	0.671	1.845	**0.00**
pg1	21236272.000	822009.400	0.10
pg2	17.364	19.429	**0.00**
pg3	23.335	3.165	**0.00**
pg4	40.416	3.972	**0.00**
pg5	14.210	0.599	**0.00**
tcop	0.015	0.042	**0.00**
ctcts	33.847	15.148	**0.00**
tcgc	0.240	0.660	0.10
tcmm	0.008	0.021	**0.00**
trade	1.682	1.882	**0.00**
pawsss	32121211.000	14375870.000	0.40
patss	84203092.000	6683619.000	0.30
agef	39.582	4.218	**0.00**
psns	102.999	5.122	0.10
dcomp	0.000	0.000	**0.00**

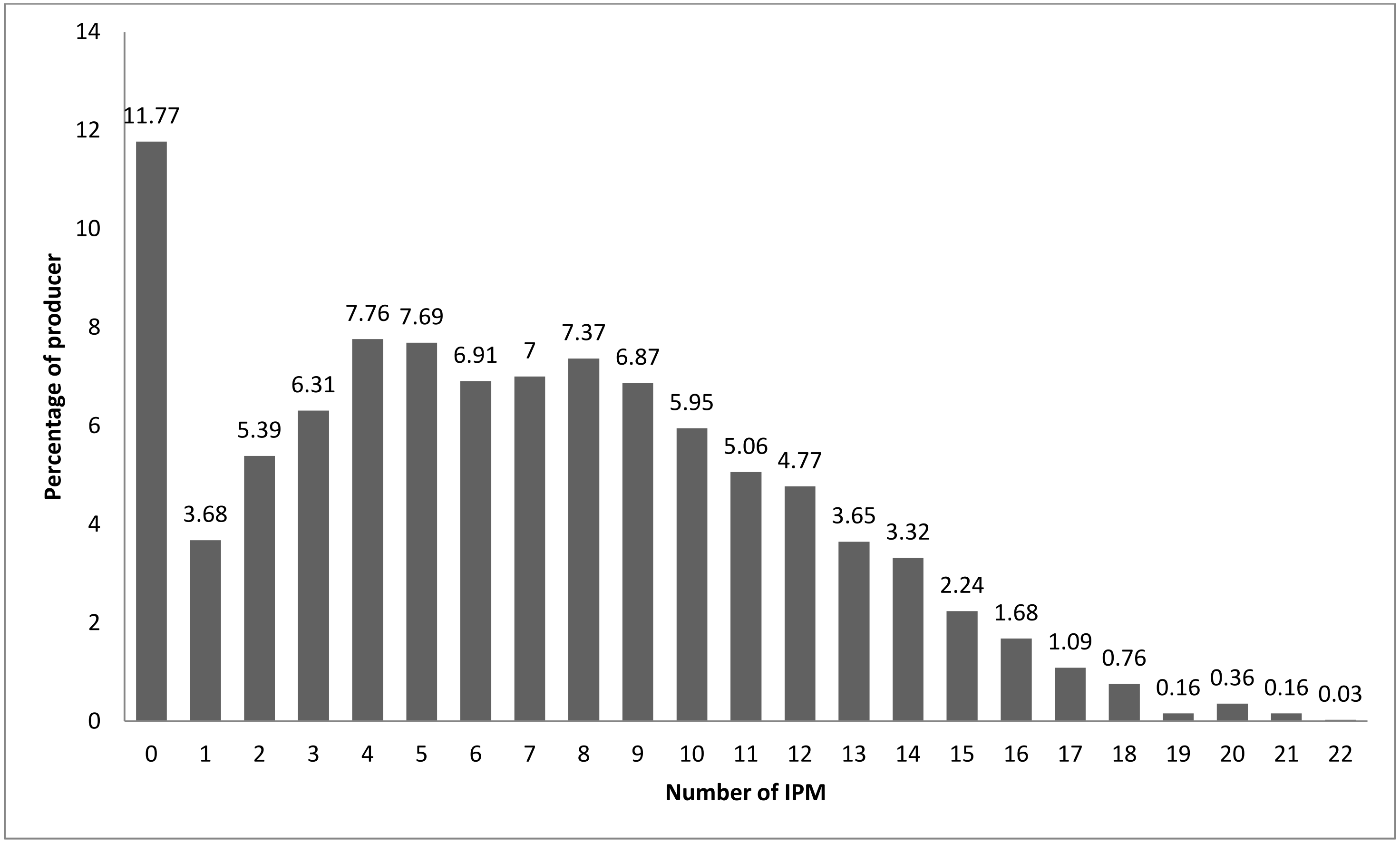

Figure 1: Percentage of nursery producers adopting different numbers of IPM.

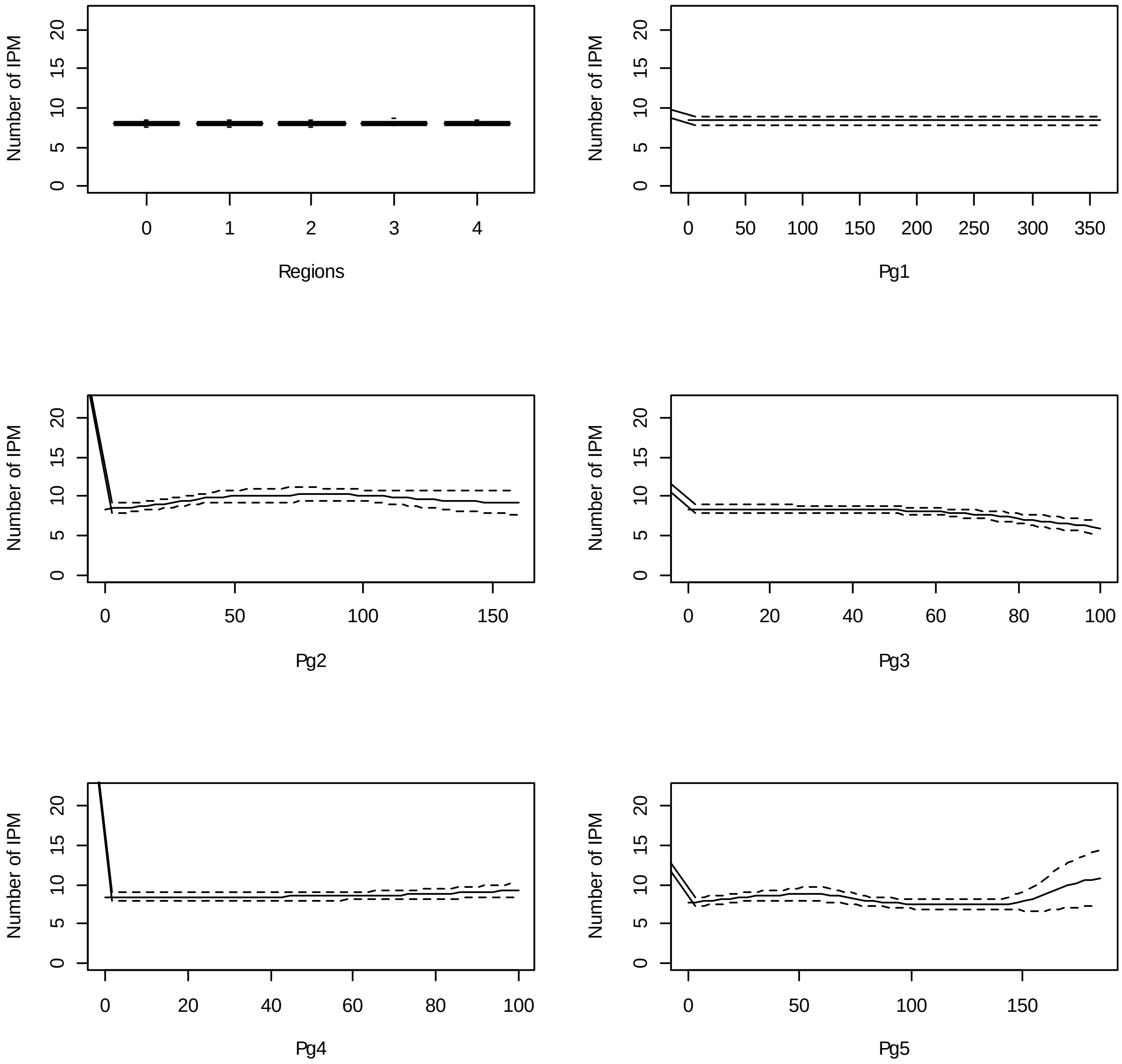

Figure 2: Nonparametric model partial regression plots (Note: Estimated Nonparametric line parallel to horizontal axis implies that the variable does not affect the number of IPM adoption).

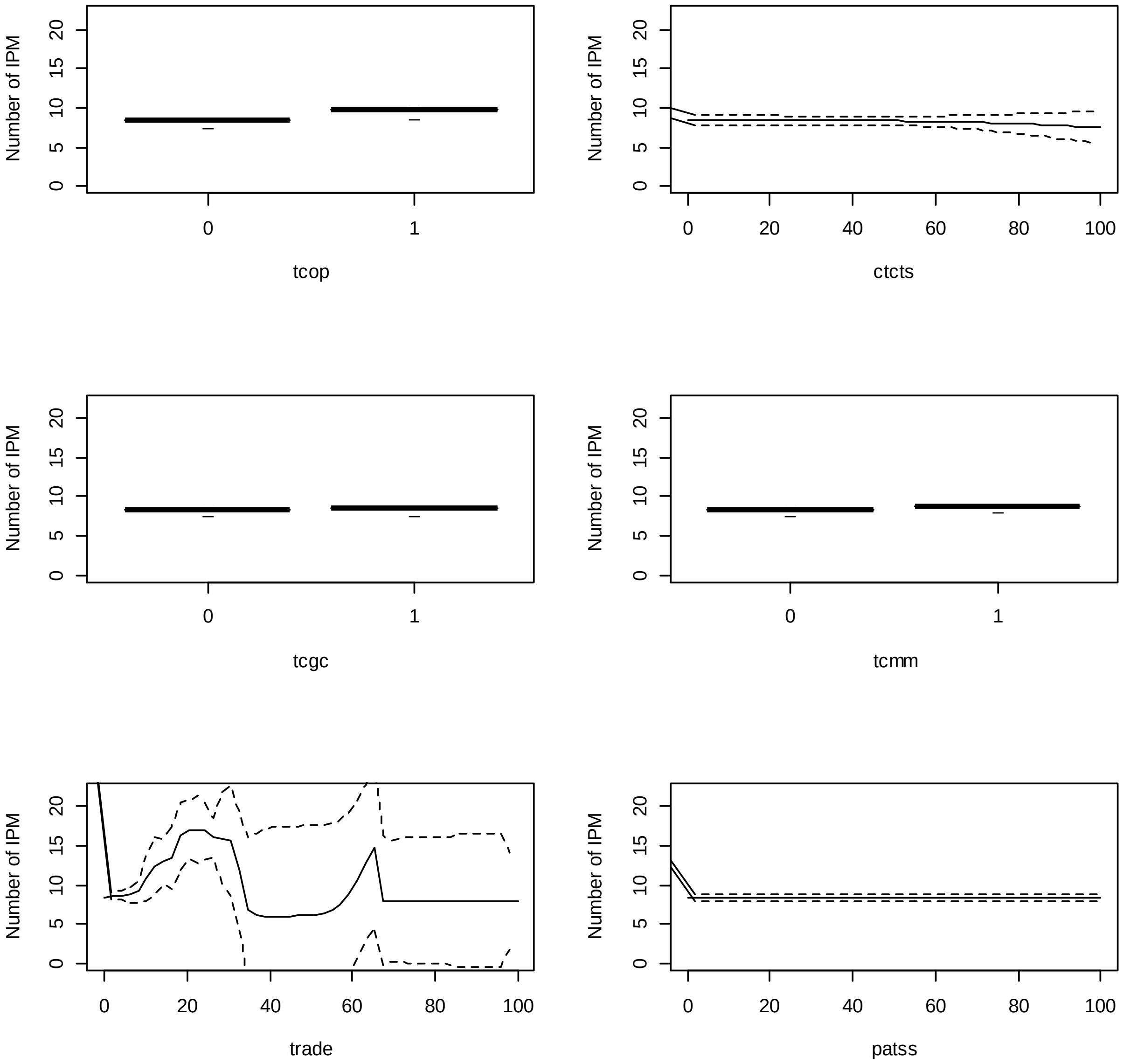

Figure 2: Contd.

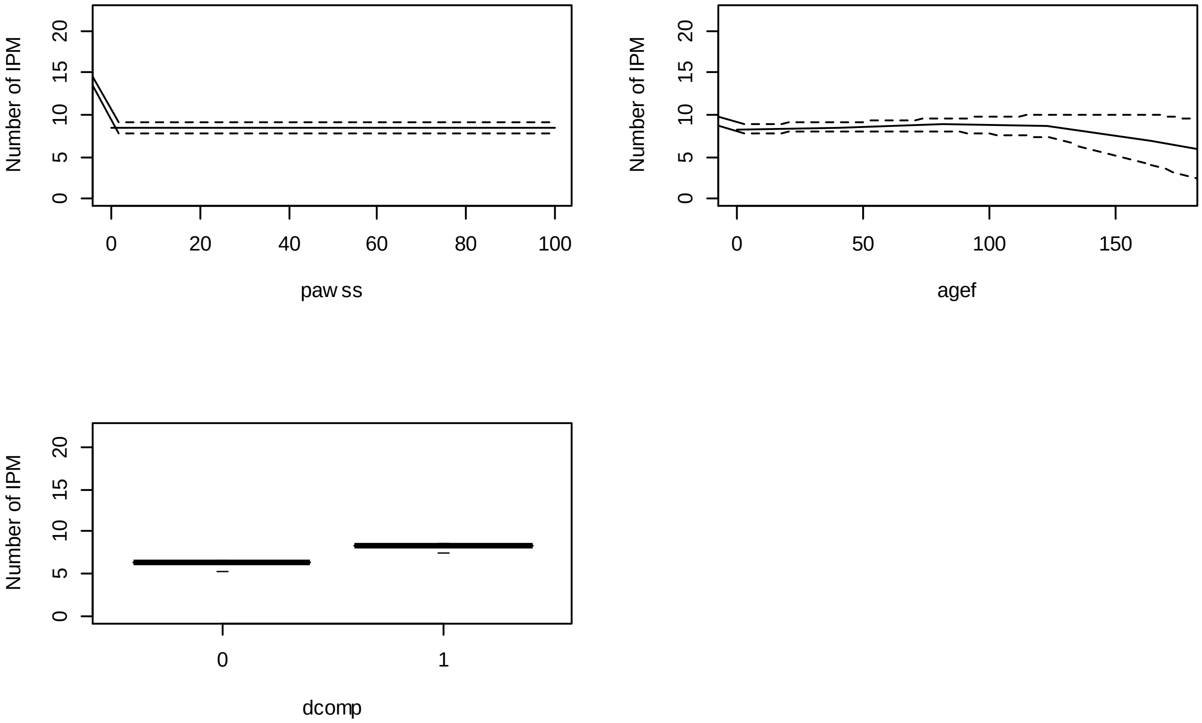

Figure 2: Contd.