The Role of Integrated Pest Management Practices in the U.S. Nursery Industry: A Bayesian Hierarchical Poisson Approach

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1. Introduction

The U.S. nursery industry has experienced unprecedented growth and innovations, which was reflected by substantial increases in sales revenues in the last two decades (Hall, Hodges, and Palma, 2011). Pest management has then become an important part of the nursery production systems in the U.S. in terms of cost and time savings (Pandit, Paudel, and Hinson, 2012). Recently, due to the increasing chemical costs, pest chemical resistance issues, and environmental impacts in the production of nursery plants, Integrated Pest Management (IPM), which include a combination of mechanical & physical control, biological control, chemical control, and cultural control, have played an essential role in solving pest problems effectively and managing ecosystem sustainably (Sellmer et al. 2004). According to the Environmental Protection Agency (EPA, 2011), IPM is defined as a sustainable approach to control and treat pests by combining different management tools while minimizing its economic, health, and environmental risks. Since the inception of IPM practices in 1972, results from empirical literatures have demonstrated that a systematic use of IPM practices can benefit greenhouse and nursery growers by producing healthy nursery plants while reducing environmental risks and associated pesticide costs (Fulcher and White 2012, Fernandez-Cornejo and Ferraioli 1999, Raupp and Cornell 1988). A lot of evidence is showed that IPM practices can increase production efficiency and improve nursery firm's profitability (Burkness and Hutchison, 2008; Fernandez-Cornejo, 1996). Recently, Alston (2011) also found that the health conditions for both workers and consumers can be greatly improved through adopting more efficient and environmental friendly IPM practices.

Although a lot of studies have been focused on IPM technology adoptions in agriculture, most of them are dealt with food crops and few has been analyzed the relationship between firm's characteristics and the IPM practice adoptions in the U.S. nursery industry. Recently, Li et al. (2013) examined how grower's characteristics influenced the adoption of IPM in greenhouse and nursery production, but their research was limited only in three northeast states in the U.S. In addition, many studies on IPM technology adoptions in agriculture were analyzed by count data models using maximum likelihood estimations (Mishra and Park 2005, Paxton et al. 2011, Pandit, Paudel, and Hinson 2012). Count data are usually modeled with Poisson regression. However, it is well-known that count data are often over-dispersed (i.e. there are extra-variability than the expected counts), which makes Poisson model inadequately fit the data (King, 1989). Although negative binomial regression is a good way in dealing with over-dispersion by the frequentist method, the dispersion parameter estimated by maximum likelihood is usually not robust, which can cause bias and result in incorrect statistical inferences (Lloyd-Smith, 2007).

Compared with frequentist methods which rely on asymptotic approximation and assume unknown parameters are fixed, Bayesian methods, which provide another way to treat parameters as random variables and make probability statements about parameters based on Bayes' theorem, are gaining more popularities in the applied agricultural researches (Du,Yu, and Hayes, 2011). Kuhner (2006) argued that Bayesian approach is more accurate by combining appropriate prior information in the data within a solid theoretical framework. Bornn and Zidek (2012) pointed out it can estimate any parameter of the functions directly and provide interpretable results in terms of probabilities. Furthermore, with a concern on missing values in the survey such as national nursery survey, Bayesian approach can reduce estimation bias and risk to some degree through parameter simulations. There are many examples of utilizing

Bayesian methods in applied studies (e,g. Sparks and Campbell, 2014; Du,Yu, and Hayes, 2011; Chib, Nardari and Shephard, 2002; Ouedraogo and Brorsen, 2014).

Understanding nursery firm's IPM adoption behavior is important and useful in terms of expanding sustainability, and gaining more government/agency supports and investments on the effective and environmental friendly IPM practices. Therefore, in order to account for nursery firm's heterogeneity, incorporate prior information, and capture parameter uncertainty, this paper applies a Hierarchical Poisson model from a Bayesian perspective to analyze the relationship between nursery firm's characteristics and the adoption of sustainable IPM practices in nursery production. Different Bayesian specifications are compared and tested, where the selection is based on deviance information criterion (DIC). Hence, the rest of the paper is organized as follows. The data source and its structure is described in section 2. In section 3, the detailed Bayesian Hierarchical Poisson regression method is reviewed and discussed. In section 4, discussion focuses on the posterior inferences and policy implications. Lastly, section 5 provides a summary and conclusion.

2. Data Source

Data for this research was obtained from the 2009 U.S. National Nursery Survey, which was conducted by the Green Industry Research Consortium, consisting of a group of agricultural economists and horticulturalists. Since its inception in 1989, the 2009 survey is the fifth effort to collect comprehensive data about greenhouse and nursery product types, production and management practices, marketing practices, and regional trades in nursery products. In 2009, a total of 3,044 firms responded from a randomly selected sample of 17,019 firms in all 50 states, with an 18% response rate (Hall, Hodges, and Palma 2011).

Twenty-two different Integrated Pest Management (IPM) practices were listed in Table 1. More than 50% of the respondents used IPM practices of removing infested plants, using cultivation & hand weeding, spot treatment with pesticides, and alternating pesticides to avoid chemical resistance. Figure 1 summarized the number of IPM practices used by nursery firms. We can see that the majority of nursery firms adopted from 4 to 10 IPM practices and more than 150 firms used 8 IPM practices. Firms with gross sales revenues less than $10,000 were excluded from the data analysis in order to match with the industry reporting procedure of USDA. The firm size (large or small) was determined based on the gross sales revenue with the threshold of $500,000 (Hinson et al., 2012). Indicator variables including multiple forward contracts (*forward*) and computer technology usage (*comscore*) were created if there was more than one type of buyer for forward contracting, and more than 3 computerized functions used respectively (Hinson et al., 2012). Other dummy variables affecting management and planning such as product uniqueness (*product*) and ability to hire competent management (*ability*) were also created based on the rating scales in the survey. After cleaning up the incorrect entries and missing values, a total of 1672 firms will be used in this analysis.

In the study, I will investigate the primary factors that influence the number of IPM practice adoptions by nursery firms. The outcome variable is the number of IPM practices (*ipm*). Explanatory variables hypothesized to influence the number of IPM practices consist of firm size ($firm\_size$), number of years in operation (*age*), numbers of trade show attended (*tradeshow*), computer technology usage (*comscore*), brokering plants form other growers (*broker*), product uniqueness (*product*), multiple forward contracts (*forward*), ability to hire competent management (*ability*), and regions which include Northeast (*region_northeast*), South (*region_south*), West (*region_west*), and Midwest (*region_midwest*). Variable names and

descriptive statistics are provided in Table 2. The baseline Poisson model can be presented by the following equation:

$$\log\big(E(ipm|X)\big) = \beta_0 + \beta_1 size + \beta_2 age + \beta_3 comscore + \beta_4 tradeshow + \beta_5 broker + \beta_6\, product + \beta_7\, forward + \beta_8 ability + \beta_9 region_{northeast} + \beta_{10} region_{south} + \beta_{11} region_{west} \quad (1)$$

3. Method

The Poisson distribution is often used to model the number of events occurring randomly through a fixed time or space interval (Cameron and Trivedi, 2005; Frank, 1967). It is the basic regression model for count data, and it is usually expressed as: $y_i \sim Poisson\ (\lambda_i)$, where $\lambda_i = \exp(x_i^T \beta)$, x_i=$[1, x_{i1}, \dots x_{ik}]$ is the predictor vector, and y_i is a non-negative integer. The unique feature of Poisson model is the equal-dispersion assumption, i.e. $Var(y_i) = E(y_i) = \lambda_i$. However, due to individual level heterogeneity, correlation among observations, incorrect model specifications or variance functions, count data are often over-dispersed which causes the variance greater than the mean (King, 1989; Winkelmann, 2008). Ignoring over-dispersion in the Poisson model will eventually result in underestimated standard errors and incorrect statistical inferences. There are several ways to handle this extra variability in Poisson model by frequentist methods such as quasi-likelihood Poisson regression which scales the covariance within the Poisson regression, negative binomial regression which mixes a random gamma variable with the same mean as Poisson, and Hierarchical Poisson regression which includes random effects etc. (McCullagh and Nelder, 1989; Breslow, 1984).

Hierarchical Poisson regression has the same log link function as Poisson's, but incorporates a random effect in the mean structure which is often demonstrated to be more effective and efficient in dealing with over-dispersion (Breslow, 1984). In this research, we

analyze nursery firm's IPM adoption behaviors by utilizing a Bayesian method to the Hierarchical Poisson model. We assume the number of IPM practices adopted by each nursery firm (ipm_i) follows Poisson random variable with unknown parameter λ_i (i.e. intensity or adoption rate per year):

$$ipm_i|\lambda_i \sim Poisson\ (\lambda_i) \tag{2}$$

A log link function is then used to form the linear predictors:

$$\log(\lambda_i) = x_i^T\beta + \theta_i,\ \ \theta_i \sim N\ (0, \sigma^2)\ , \tag{3}$$

where θ_i is the random effect that captures firm-level heterogeneity and accounts for over-dispersion (Breslow, 1984). The likelihood for the data given covariate matrix $\boldsymbol{X}$ and parameter vector β is the product of each Poisson PDF reflecting the additional random effect added in the model:

$$L(\boldsymbol{ipm}|\boldsymbol{X}, \beta) = \prod_{i=1}^{n} P(ipm_i|\lambda_i) = \prod_{i=1}^{n} \frac{\lambda_i^{ipm_i} e^{-\lambda_i}}{ipm_i!},\ \text{where } \lambda_i = \exp(x_i^T\beta + \theta_i) \tag{4}$$

In this Bayesian analysis, a non-informative normal prior is placed on each β_j since it is relatively flat to the likelihood function and has least influence on the posterior distributions (Lee 2004), and an inverse gamma prior with fixed shape and scale parameter is placed on the variance of the random effect θ_i (Draper, 1996):

$$\beta_j \sim N(0, 100) \tag{5}$$

$$\sigma^2 \sim igamma(0.01, 0.01) \tag{6}$$

According to Bayes rule (Carlin and Louris 2000), the posterior distribution of β given {**X,** $\boldsymbol{ipm}$} is: $p(\beta|\boldsymbol{X}, \boldsymbol{ipm}) = \frac{p(\boldsymbol{ipm}|\mathbf{X}, \beta)p(\beta)}{\int_0^\infty p(\boldsymbol{ipm}|\mathbf{X}, \beta)p(\beta)\mathrm{d}\beta}$ (i.e. posterior $\propto$ prior $\times$ likelihood).

In order to check for over-dispersion and assess goodness of fit, a Pearson's chi-square statistic $\chi_{\mathrm{P}}^2 = \sum_{i=1}^{n} \frac{(ipm_i - E(ipm_i))^2}{Var(ipm_i)}$ is calculated, and a rule of thrum for equal-dispersion is that

the Pearson's chi-square statistic/d.f. approximately equals to one (McCullagh and Nelder, 1989). If over-dispersion is present and significant in the data, a Bayesian framework of negative binomial regression is also estimated and compared with Bayesian Hierarchical Poisson regression in terms of deviance information criteria (DIC), which is a Bayesian alternative to Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) assessment tools, and a smaller DIC usually indicates a better fit for the data (Spiegelhalter et al. 2002). For Bayesian negative binomial model, we assume $ipm_i|\mu, k \sim NB\ (\mu, k)$. It naturally accounts for over-dispersion since the variance estimate (i.e. $Var(ipm_i) = \mu + k\mu^2$) is always greater than for Poisson distribution with same mean (i.e. $\mathrm{E}(ipm_i) = \mu = \exp(x_i^T\beta)$) (Faraway,2006). Non-informative normal priors are placed on β with $\beta_j \sim N(0, 100)$, and a gamma prior with fixed shape and scale parameter is placed on the dispersion parameter k: $k \sim gamma(0.001, 0.001)$.

Since the exact inference may not always be guaranteed (i.e. posterior distribution does not have a closed form), in this application, a stochastic simulation method-Markov Chain Monte Carlo (MCMC) is used to sample posterior distributions and make posterior statistical inferences (Robert and Casella 2004). In this research, we first generate 200,000 Gibbs samplers with a burn-in of 10,000 iterations. Due to high autocorrelation introduced via the Gibbs sampling, we then control the thinning rate of the simulation by keeping every 5th of the iterations for calculating all the posterior estimates including posterior means, posterior standard deviations, and 95% highest posterior density (HPD) etc. Finally we check the Markov Chain convergences such as trace plots, autocorrelation plots, and kernel density plots etc.

4. Results

All inferences about coefficients β were based on posteriors $p(\beta|\boldsymbol{X}, \boldsymbol{ipm})$. Table 3 provided the result of Poisson regression from the Bayesian perspective. The p-value (i.e. less than .001) of the Pearson chi-square statistic indicated that there was a greater variability among the IPM practice counts than would be expected for Poisson distribution (i.e. over-dispersion), so the Poisson model didn't fit the data well. The Bayesian Hierarchical Poisson regression was then estimated and summarized in Table 4. Compared with Bayesian Poisson regression in Table 3, the parameter estimates were similar, but an inflated covariance matrix affected standard errors, and hence p-values in a conservative way. From the goodness of fit measures in Table 4, we can see that the Pearson chi-square statistic significantly decreased with a large p-value of 0.922, and the value of DIC was much smaller than that of Bayesian Poisson model in Table 3, which suggested that the Bayesian Hierarchical Poisson model fitted the data adequately. In addition, in comparison with negative binomial regression from Bayesian standpoint in Table 5, the value of DIC in Table 4 was still lower, which again confirmed that Bayesian Hierarchical Poisson model was superior in capturing over-dispersion and accounting for unobserved heterogeneity in this study. The diagnostic plots including trace, autocorrelation, and kernel density plot for each covariate were provided in Figure 2, which demonstrated all excellent convergence and good mixing of the MCMC samplers by Bayesian Hierarchical Poisson model. The regression results of negative binomial and hierarchical Poisson using maximum likelihood estimations were also provided in Table 7 for references.

The posterior summary which included mean, standard deviation, percentiles, and 95% highest posterior density (HPD) for Bayesian Hierarchical Poisson model was presented in Table 4. We found that except for *age* and *region_west*, all the other covariates were positive and

significant at 5% level in the model. Based on the estimated rate ratios in Table 6, large nursery firms (i.e. sales revenue were above $500,000) had about 7.1% higher IPM adoption rates than those of small nursery firms. This was intuitively explained since large firms usually had finical and research abilities to invest and benefit more from new technologies in IPM methods, which suggested that local governments and research agencies (i.e. university extensions) should target more small sized firms on resource availabilities, education programs, and even utilization of some financial rewards to widely encourage IPM practice uses. We found that there was an estimated 6.7% increase in rate of IPM adoption for those firms who resold or brokered plants form other growers. One possible reason was that firms who expanded their business and increased sales through brokering would spent more time and money on investing cost-effective and efficient IPM practices. A one more increase in the number of trade shows attended by nursery firms would raise their IPM adoption rates by 0.8%. The trade show was often a good platform in nursery industry to showcase new products and equipment, absorb new innovations and technologies, promote sales and attract more customers. Hence, suggestions like providing discount prices for exhibitions/registrations and offering certificates/awards by state/regional nursery associations can attract more firms to attend the trade fairs, which would eventually benefit nursery firms by utilizing more sustainable IPM practices in the long run. As compared to firms who located in the Midwest region, IPM adoption rates were about 10.4% higher for firms located in both Northeast and South regions. Since both of those regions have experienced rapid growth in terms of sales revenues recently, this result indicated that more information, research, and education programs should be concentrated on West, and especially Midwest region in order to encourage the effective and environmental fridnely IPM practice adoptions. In addition, IPM practice intensities were about 15% higher for firms who rated their product uniqueness as a very

important factor affecting their management and planning. Similarly, IPM intensities were 7.3% higher for firms who indicated a higher importance rating on their ability to hire competent management as a factor in impacting their business. As expected, firms who focused more on product uniqueness would make great efforts on improving their plant's health and nutrition, and hence investing and adopting more economical and effective IPM practices. Similarly, if firms were able to hire competent management, they would utilize more cost-effective and efficient IPM practices to treat their pest problems. Furthermore, firms who used multiple forward contracts (*forward*) and more computerized functions in assisting with their production (*comscore*) can greatly increase their IPM adoption rates. For instance, there were around 31.7% and 28.5% increase in rate of IPM adoption for nursery firms who intensively used computer technologies, and who had multiple type of forward contracts respectively. Forwarding contracts can be very useful in expanding firm's markets, increasing their sales and growth while minimizing firm's risks by specifying a guaranteed price, quantity, and quality. Therefore, this indicated that having multiple forward contracts with different buyers would motivate firms to invest and apply more economical and effective IPM practices for quality assurances. The findings also suggested that local nursery associations and research centers could provide more computer technology trainings or workshops to promote more sustainable IPM practices utilized by nursery firms.

5. Conclusion

Given the increasing concerns on sustainability, and potential advantages of the effective, economical, and environmentally sustainable IPM practices, this research explored the relationship between nursery firms' characteristics and adoptions of IPM practices by utilizing a recent national nursery survey. In order to account for firm's heterogeneity, incorporate prior information in the estimation, capture parameter uncertainties and reduce biases due to large amount of missing information in the data, we applied a Bayesian Hierarchical Poisson regression with MCMC Gibbs sampling algorithms. In this study, we demonstrated that Bayesian Hierarchical Poisson model was robust and superior in capturing over-dispersion as compared to Poisson and negative binomial models from Bayesian frameworks.

We identified several positive and significant factors affecting the rate of IPM adoption, and our results suggested that considerable marketing effects should be made on educating and encouraging small firms (i.e. sales revenue were below $500,000) to adopt more efficient and sustainable IPM practices in the West and Midwest regions. In addition, we found that the IPM adoption rates were higher for firms who had higher importance ratings on their product uniqueness and ability to hire competent management. Moreover, nursery firms who brokered plants from other growers or had multiple forward contracts with buyers often applied more IPM practices than those firms who didn't. Furthermore, we also observed that the more computerized functions used by firms, the greater impacts on IPM practice adoptions would be. Therefore, local governments and research agencies could target on offering some training courses/workshops of computer technology applications so as to motivate more adoptions of IPM practices by nursery firms. However, this research also had a limitation since it was based

on a single cross-sectional data. Future research could focus on modeling how the rate of IPM adoption is changed over time if a rich longitudinal data is available.

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Table 1: List of IPM Practices

IMP Practice Used	Percent of Respondents
A. Remove infested plants	74.1%
D. Use cultivation, hand weeding	66.0%
N. Spot treatment with pesticides	62.3%
B. Alternate pesticides to avoid chemical resistance	51.5%
L. Inspect incoming stock	49.5%
C. Elevate or space plants for air circulation	48.2%
O. Ventilate greenhouses	34.4%
J. Use mulches to suppress weeds	33.4%
M. Manage irrigation to reduce pests	31.5%
R. Adjust fertilization rates	31.0%
I. Adjust pesticide applic. to protect beneficial insects	30.7%
V. Use pest resistant varieties	29.9%
E. Disinfect benches/ground cover	28.9%
K. Beneficial insect identification	24.1%
H. Monitor pest population with tarp/sticky boards	20.8%
Q. Keep pest activity records	17.7%
T. Use bio pesticides / lower toxicity	15.5%
P. Use of beneficial insects	14.7%
G. Soil solarization/sterilization	8.7%
S. Use screening/barriers to exclude pests	8.3%
U. Treat retention pond water	3.8%
F. Use sanitized water foot baths	2.2%

Table 2: Variable Description and Summary Statistics

Variable	Description	Mean	Std. Dev.	Min	Max
ipm	Number of IPM practices adopted (0-22)	8.405	4.395	0.000	22.000
firm_size	Firm size (1 if large, 0 otherwise)	0.410	0.492	0.000	1.000
age	Firm age in terms of 2009	27.511	21.588	0.000	177.000
tradeshow	Number of trade shows attended	1.621	3.634	0.000	98.000
comscore	Computer technology usage (1 if more than 3 functions used, 0 otherwise)	0.545	0.498	0.000	1.000
broker	Resell or broker plants form other growers (1 if Yes, 0 otherwise)	0.418	0.493	0.000	1.000
product	Product uniqueness (1 if rated greater than 3, 0 otherwise)	0.647	0.478	0.000	1.000
forward	Forward contract types (1 if more than 1, 0 otherwise)	0.061	0.240	0.000	1.000
ability	Ability to hire competent management (1 if rated more than 3, 0 otherwise)	0.162	0.369	0.000	1.000
region	Northeast, South, West, Midwest	2.376	0.939	1.000	4.000

Table 3: Posterior Summary Result for Bayesian Poisson Regression

Parameter	**Mean**	**Std. Dev.**	**Percentiles**			**95% HPD Interval**	
			25%	**50%**	**75%**	Lower	Upper
Intercept	1.685	0.030	1.665	1.685	1.705	1.624	1.740
firm_size	0.068	0.020	0.055	0.068	0.081	0.030	0.107
age	0.001	0.000	0.001	0.001	0.001	-0.000	0.002
comscore	0.265	0.019	0.253	0.265	0.278	0.227	0.302
tradeshow	0.007	0.002	0.005	0.007	0.008	0.003	0.010
broker	0.057	0.017	0.045	0.056	0.069	0.023	0.090
product	0.131	0.019	0.119	0.131	0.144	0.096	0.168
forward	0.239	0.030	0.217	0.239	0.259	0.179	0.297
ability	0.068	0.022	0.054	0.068	0.083	0.023	0.111
region_ northeast	0.092	0.029	0.071	0.092	0.111	0.038	0.150
region_south	0.095	0.025	0.078	0.095	0.112	0.048	0.146
region_west	0.069	0.029	0.050	0.069	0.088	0.012	0.124
χ_{P}^{2} [1]	3315.800	30.519	3293.800	3314.500	3335.200	3256.400	3374.000
DIC[2]	9987.670						

Note: 1: Pearson Chi-Square Statistic with a p-value less than .001
2: Deviance Information Criterion (DIC)

Table 4: Posterior Summary Result for Bayesian Hierarchical Poisson Regression

Parameter	**Mean**	**Std. Dev.**	**Percentiles**			**95% HPD Interval**	
			25%	**50%**	**75%**	Lower	Upper
Intercept	1.602	0.044	1.571	1.601	1.631	1.518	1.688
firm_size	0.069	0.028	0.050	0.069	0.087	0.014	0.122
age	0.001	0.001	0.001	0.001	0.001	-0.000	0.002
comscore	0.275	0.028	0.256	0.275	0.294	0.221	0.329
tradeshow	0.008	0.003	0.006	0.008	0.010	0.002	0.015
broker	0.065	0.025	0.048	0.065	0.082	0.016	0.114
product	0.140	0.026	0.122	0.140	0.157	0.090	0.192
forward	0.251	0.048	0.219	0.251	0.283	0.155	0.341
ability	0.071	0.034	0.048	0.070	0.093	0.005	0.138
region_ northeast	0.099	0.045	0.069	0.099	0.130	0.007	0.183
region_south	0.099	0.038	0.073	0.099	0.124	0.028	0.174
region_west	0.064	0.042	0.036	0.064	0.092	-0.016	0.149
σ^2	0.130	0.010	0.123	0.130	0.136	0.112	0.150
χ_{P}^{2}[1]	1579.900	74.731	1528.800	1579.000	1629.700	1428.100	1723.300
DIC[2]	9137.019						

Note: 1: Pearson Chi-Square Statistic with a p-value of 0.922
2: Deviance Information Criterion (DIC):

Table 5: Posterior Summary Result for Bayesian Negative Binomial Regression

Parameter	**Mean**	**Std. Dev.**	**Percentiles**			**95% HPD Interval**	
			25%	**50%**	**75%**	Lower	Upper
Intercept	1.680	0.045	1.649	1.679	1.709	1.591	1.767
firm_size	0.065	0.029	0.045	0.065	0.084	0.004	0.118
age	0.001	0.001	0.001	0.001	0.001	-0.000	0.002
comscore	0.263	0.028	0.245	0.263	0.282	0.210	0.318
tradeshow	0.008	0.004	0.006	0.008	0.011	0.001	0.016
broker	0.060	0.025	0.043	0.059	0.077	0.011	0.112
product	0.136	0.027	0.119	0.136	0.154	0.080	0.186
forward	0.247	0.050	0.214	0.247	0.281	0.150	0.342
ability	0.072	0.034	0.050	0.072	0.095	0.007	0.141
region_ northeast	0.096	0.045	0.066	0.096	0.126	0.005	0.180
region_south	0.095	0.038	0.070	0.096	0.121	0.020	0.167
region_west	0.070	0.043	0.042	0.070	0.100	-0.013	0.154
k[1]	0.138	0.004	0.135	0.138	0.141	0.131	0.144
DIC[2]	9470.988						

Note: 1: Dispersion parameter
2: Deviance Information Criterion (DIC)

Table 6: Rate Ratio Estimates and 95% HPD Intervals from Bayesian Hierarchical Poisson Regression

Covariate	**Estimate**	**95% HPD Interval**	
		Lower	**Upper**
firm_size	1.071	1.014	1.129
age	1.001	0.999	1.002
comscore	1.317	1.247	1.390
tradeshow	1.008	1.002	1.015
broker	1.067	1.016	1.121
product	1.150	1.090	1.207
forward	1.285	1.168	1.406
ability	1.073	1.005	1.148
region_northeast	1.104	1.008	1.201
region_south	1.104	1.026	1.187
region_west	1.066	0.979	1.156

Table 7: Results of Maximum Likelihood Estimates for Negative Binomial and Hierarchical Poisson Regressions

	Negative Binomial			**Hierarchical Poisson**		
Parameter	**Estimate**	**Std Err**	**P-Value**	**Estimate**	**Std Err**	**P-Value**
Intercept	1.682	0.044	<.0001	1.683	0.042	<.0001
firm_size	0.065	0.029	0.025	0.065	0.027	0.018
age	0.001	0.001	0.087	0.001	0.001	0.074
comscore	0.263	0.028	<.0001	0.263	0.027	<.0001
tradeshow	0.008	0.004	0.020	0.008	0.003	0.006
broker	0.059	0.025	0.020	0.059	0.024	0.016
product	0.135	0.027	<.0001	0.134	0.026	<.0001
forward	0.246	0.049	<.0001	0.245	0.047	<.0001
ability	0.072	0.033	0.030	0.072	0.032	0.025
region_ northeast	0.095	0.044	0.032	0.094	0.043	0.027
region_south	0.094	0.036	0.010	0.094	0.035	0.007
region_west	0.069	0.042	0.100	0.069	0.040	0.088
k[1]	0.137	0.010				
σ^2				0.118	0.008	

Note: 1: Dispersion parameter

Figure 1: Number of IPM Practices Used by Nursery Firms

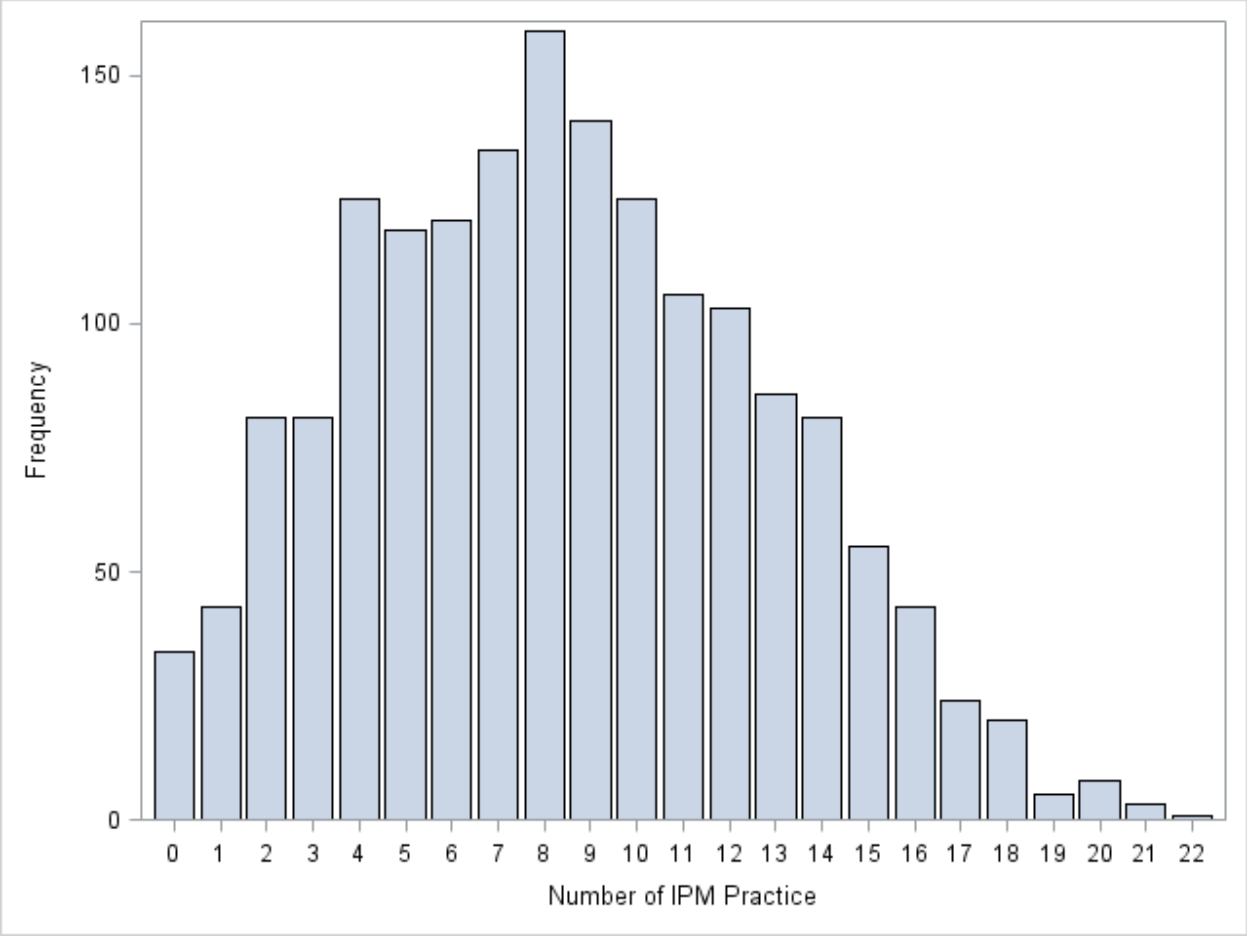

Figure 2: Convergence Diagnostic Plots for Each Covariate Based on Bayesian Hierarchical Poisson Regression

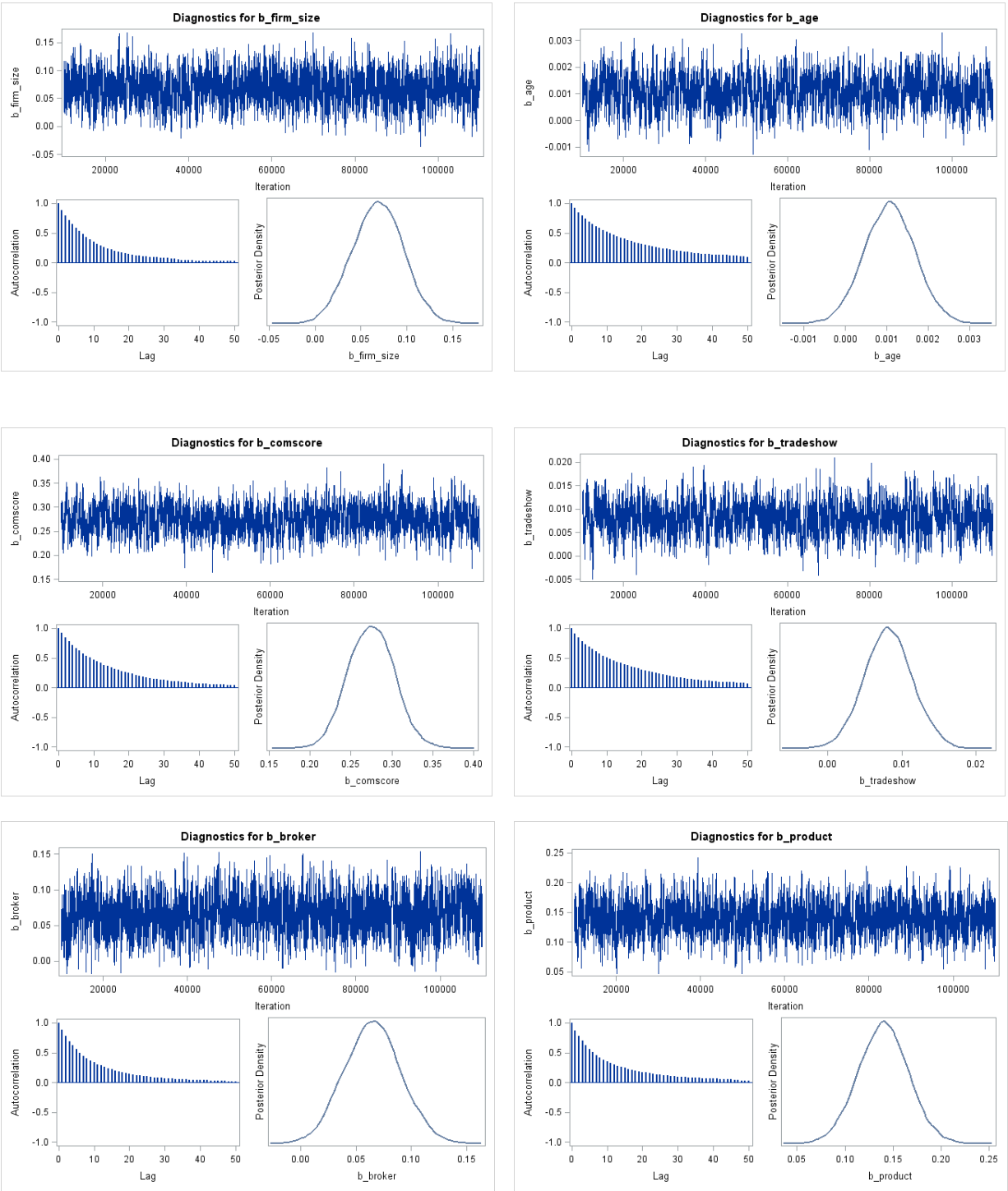

Figure 2: Convergence Diagnostic Plots for Each Covariate Based on Bayesian Hierarchical Poisson Regression (Continued)