The Impact of Integrated Pest Management Practices on U.S. National Nursery Industry Annul Sales Revenue: An Application of Smooth Transition Spatial Autoregressive Models

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Introduction

The U.S. nursery industry has progressed substantially in the last two decades, becoming one

of the fastest growing industries in U.S. agriculture (Hall, Hodges, and Palma, 2011). Nursery

products include trees/shrubs, vines, bedding plants, foliage and other plants. According to the 2009

National Nursery Survey, the largest regions and states in terms of total annual sales were the Pacific

and Southeast regions (led by California and Florida, respectively), which accounted for about 49%

of the total sales in 2008. The whole nursery industry was influenced by many factors such as the

quality of agricultural land, weather conditions, production and management practices, marketing

practices, and regional trade, to name only a few (Hall et al., 2011). Numerous studies have been

conducted to investigate trade dynamics, marketing practices and financial and economic factors that

contribute to the U.S. nursery industry sales. For instance, Johnson and Jensen (1992) identified and

measured the effects of economic indicators on the U.S nursery products sales by geographical and

statistical methods. Guo, Yue, and Hall (2011) used gravity models to investigate how distance,

economic conditions and business characteristics affected the trades in the U.S. national nursery

industry. Palma et al. (2011) examined the effectiveness of nursery firms' promotion and

advertising expenditures on sales. Campbell, Hall and Combs (2009) found that marketing and

advertising expenses played an impartment role in the total nursery sales from 1988-2003.

Recently, due to the increasing chemical costs, pest chemical resistance issues, and

environmental impacts in the production of nursery plants, Integrated Pest Management (IPM)

practices, which include mechanical control, biological control, pesticide control, and other controls,

have become an essential part of the nursery production systems (Sellmer et al. 2004). Fulcher and

White (2012) defined IPM as a "sustainable approach to managing pests by combining biological,

cultural, and chemical tools in a way that minimizes economic, aesthetic, health, and environmental

risks." Results from empirical literature showed that a systematic use of IPM practices can benefit greenhouse and nursery growers by producing healthy nursery plants while reducing the amount of water pollutions (Fulcher and White, 2012; Fernandez-Cornejo and Ferraioli, 1999; Raupp and Cornell, 1988). Some studies have focused on IPM technology adoptions and especially their intensities in the agriculture through count data models (Fernandez-Cornejo and Ferraioli, 1999; Mishra and Park, 2005; Pandit, Paudel, and Hinson, 2012; Paxton et al., 2011).

However, few studies investigated the relationship between IPM practices and nursery sales revenue. Although Hodges et.al. (2008) reported that production practices and technology use in the U.S. nursery industry differ across regions in terms of economic returns and environmental impacts, yet no theoretical and applied econometric methods were developed to provide evidence for spatial heterogeneity in economic and environmental impacts. Understanding the sources and extent of geographic heterogeneity is important for accurately modeling and forecasting economic growth. By appropriately modeling heterogeneity, insight about connections to wider economies and specific solutions to region-wide resource allocation problems is possible.

Economic geographies are normally characterized by spatial heterogeneity (Anselin, 1988). Heterogeneity may be caused by different production functions, systematically varying parameters, or heteroskedasticity associated with spatial regimes (Anselin, 1988). For instance, commodity price transmission may be region-specific (Vitale and Bessler, 2006), skilled labor may be concentrated in certain locations (Davis and Schluter, 2005), or industry information spillovers may be realized more frequently in agglomeration economies (Cohen and Paul, 2005). In general, geographic heterogeneity typically implies structural breaks across space (Ertur, LeGallo, and Baumont, 2003). Heteroskedasticity (or non-constant variance between spatial units) and may also be caused by spatial regimes (Anselin, 1988). Different geographical scales may account for heterogeneity, which

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in turn affects the magnitude of spatial spillover effects (Magrini, 2004). Measurement error or misspecification of spatial units may cause heteroskedasticity, which in turn may be a source of spatial autocorrelation (Kelejian and Robinson, 2004). Spatial heterogeneity may also be associated with spatially varying parameters generated by spatially dependent functional forms (Pace et al., 2004).

For the reasons discussed above, this paper applies a relatively new class of spatial regression models – the Smooth Transition Autoregressive (STAR) models – which allow for endogenous sorting of spatial units into different regimes. The approach is especially useful for modeling for the effects of advertising expenditures on nursery sales as a data-driven process. Based on national nursery survey data collected in 2009, we investigated the primary factors which influenced U.S. nursery sales. Twenty two IPM practices were combined into seven major categories, which were used in an econometric model to measure the extent to which IPM groups were associated with nursery sales, controlling for selected production, management, and marketing practices related variables. Some IPM groups may have positively contributed to the annual sales through their backward and forward linkages. But in other areas, different IPM groups may have no effect, or even a negative impact, on annual sales. Identifying specific IPM groups that contributed to annual sales may provide practical insight about strategies to reduce production costs and increasing overall economic viability. The hypothesis that nursery industry sales are geographically heterogeneous by IPM groups was tested using Smooth Transition Spatial Process models. This class of models exhibiting regime switching behavior is useful for identifying the adoption of IPM practices, providing another tool for exploring relationships between geographical determinants and total sales.

Data and Baseline Model

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 collecting comprehensive data about greenhouse and nursery product types, production and management practices, marketing practices, and regional trade 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 et al., 2011).

Twenty-two Integrated Pest Management (IPM) practices with their percentage of respondents were listed and calculated from this survey (Table 1). According to its similar characteristics and natures, we categorized those 22 IPM practices into 8 different groups: Biological Control (BC), Fertilization Rate (FR), Monitoring (M), Mechanical Control (MC), Pesticide Control (PC), Preventive Practices (PP), Water Rate (WR), and others (Table 1). After excluding missing, and/or incomplete observations from the sample, a total number of observations were reduced to 809. The response variable is the log of annual sales in 2008. Predictors hypothesized to influence national nursery industry annul sales include the number of years in operation, firm sizes, use of computer technology in nursery operations which is scored from 0 to 100, 8 IPM groups (others is the reference group) , percentage of wholesale sales, and percentage of advertising budget (internet, printed materials, mass media and others). The baseline log-linear model can be presented by the following equation:

(1) lnsales=β_0+$\beta_1 \cdot age + \beta_2 \cdot class + \beta_3 \cdot comscore + \beta_4 \cdot wholesale + \beta_5 \cdot tradeshow + \beta_6 \cdot internet + \beta_7 \cdot printed + \beta_8 \cdot mass + \sum_k \theta_k \cdot IPM_k + u$, $k = 1$ to 7 Variable names and descriptive statistics are summarized in Table 2.

Models for Spatial Dependence and Heterogeneity

Spatial Process Models

The issue of heterogeneity across space and the potential for spatial regime "switching" behavior is further complicated when changes in the IPM groups in one nursery firm are a function of changes in neighboring nursery firms, or when unobserved factors are correlated across spatial units. In this paper, the hypothesis is that annual total nursery sales may be simultaneously determined by sales in neighboring firms. For example, $\sum_{j=1, i \neq j}^{n} w_{ij} y_j$, where W denotes spatial connectivity (i.e., spatial weights). Feedback between spatial units may be significant, meaning that sales in one firm is dependent on or explained by sales in surrounding firms. Significant interaction suggests information spillovers, thick labor markets, or forward-backward linkages to other spatial units (Anselin, 2002; Moreno et al., 2004).

Spatial dependence is usually captured by a spatial autoregressive (SAR) lag model in which an endogenous variable is used to specify interactions between spatial units (Anselin and Florax, 1995; Whittle, 1954). The SAR model with autoregressive disturbances of order (1,1) (ARAR) includes a spatially lagged endogenous variable (Wy) and spatial autoregressive disturbances: $y = \rho Wy + X\beta + \varepsilon$, $\varepsilon = \lambda W\varepsilon + u$, u is independently and identically distributed with mean zero and covariance Ω, and W is a matrix defining relationships between spatial units (Anselin and Florax, 1995). The reduced form of the ARAR model is $y = A^{-1}X\beta + A^{-1}B^{-1}u$, where $A = I - \rho W$ and $B = (I - \lambda W)$ are lag autoregressive and error autocorrelation spatial filters respectively. The inverted matrices A^{-1} and B^{-1} are spatial multipliers which relay feedback/feed-forward effects of shocks between locations (Fingleton, 2008), distinguishing this class of models from other econometric models. When the weights are contiguity matrices or groups of observations bounded by some metric, local shocks are transmitted to all other locations, with the intensity of the shocks decaying over space. Because of the spatial multipliers, the marginal effects of the spatial process models in particular

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with SAR and ARAR models are more complicated than other econometric models. LeSage and Pace (2009) suggested a variety of approaches whereby the marginal effects can be calculated. In this research, the influence of the lag multiplier is approximated as a geometric series. For example, the "total effect" of a covariate k is the global impact of that variable on a given spatial unit; $A^{-1}(I_n \circ \beta_k) = [I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \rho^4 W^4 + \rho^5 W^5 + \dots \rho^q W^q]\beta_k$, where the order q refers to the impact of its neighbors. In the limit, A^{-1} tends to $(1e\rho)^{-1}$, so the "total" marginal effect can be written as $\beta_k^{Total} = \beta_k(1 - \rho)^{-1}$. The "indirect effect" is the difference between the total and direct effect (β_k), or the impact neighboring locations (on average) have on a given spatial unit given an incremental change in the covariate at that location; $\beta_k^{Indirect} = \frac{\rho}{1-\rho} \beta_k$. Provided a consistent covariance estimator, standard errors of the total and indirect effects can be estimated using the delta method (Greene, 2000).

Smooth Transition Autoregressive Models

Smooth Transition Autoregressive models are well-developed in the time series literature (Terasvirta and Anderson, 1992; Holt and Craig, 2006; Van Dijk and Franses, 2000) and biological sciences (Schabenberger and Pierce, 2002). This class of nonlinear regression models that exhibit endogenous switching across spatial units is less familiar to the spatial econometric literature, with some exceptions. A spatial analogue of the STAR model was presented by Gress (2004), Basile and Gress (2005) and Basile (2008). Recently, Dorfman et al. (2009) developed a model that is quite similar to the STAR approach but from a Bayesian perspective. Their approach also modeled hierarchical rather than contagious autoregressive processes. Pede, Florax, and Holt (2009) and Pede (2010) modified Lebreton's (2005) spatial version of the time series STAR model by including a spatially lagged variable in the transition function. The approach applied here is parametric and extends their work.

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Let $G(v; \gamma, c)$ be an autocatalytic function (Schabenberger and Pierce, 2002), such as the logistic function; $[1 + exp(-\gamma[v - c]/\sigma_v)]^{-1}$, with slope and location parameters γ and c, respectively, and a transition variable v. $G(v; \gamma, c)$ be a potentially smooth, real-valued transition function bounded between zero and one. The parameters are approximately scale-neutral when they are normalized by the standard deviation of the transition variable (σ_v). The model with regime-switching potential is,

(2) $Y = G \circ Z\beta_1 + (1 - G) \circ Z\beta_2 + u,$

where "$\circ$" is the Hadamard product operator, Z is a matrix of covariates, and (β_1, β_2) are coefficients corresponding with regimes 1 and 2. Equation 2 can be rearranged accordingly (Madalla, 1983);

(3) $Y = Z\beta_2 + G \circ Z(\beta_2 - \beta_1) + u, \rightarrow Y = Z\beta + G \circ Z\delta + u,$

with the interaction between the transition function and the exogenous variables (Z) permitting nonlinear parameter variation between spatial units. As γ increases, spatial units are sorted into more distinct groups. Intermediate values of γ identify spatial units along a continuum are "in transition", and vary according to the transition variable, v (for example, Figure 1). The parameter c is a location parameter that determines the inflection point on the regime splitting curve according to the transition variable. For larger values of γ (typically >100), observations are separated into two distinct regimes with the coefficients of the interaction terms (δ) the difference from the reference group mean response to local determinants (the β_1) and the alternative regime. Thus, rejection of the null hypothesis $\delta = 0$ suggests a nonlinear relationship between local covariates and nursery sales. For large values of γ, the regression model of (2) behaves similarly to what one would expect if a set of firms were identified using a dummy variable (e.g. large or small firms), and then interacted with all other explanatory variables. There are no regimes when $\delta = 0$ and the effects of the covariates are geographically invariant. Thus, with regimes, the location-specific marginal effects (ME) of the STAR model are $ME_i = \beta + G_i\delta$.

Like the Geographically Weighted Regression (GWR) and Spatial Adaptive Filters (SAF) models, estimates of the STAR model can assume different values at different locations. However, the advantage of the STAR model is that the incidental parameter problem posed by methods including GWR or SAF is circumvented and the usual robust covariance estimators can be applied to make inferential statements based on STAR results. Unlike the SAF or GWR models, nonlinear relationships across space are modeled using "autocatalytic" (or endogenous) switching functions under the STAR specification. To the extent that the STAR's autocatalytic function sorts spatial units along a continuous hierarchy, the smooth transition model also lends itself to identifying endogenous break points across space resulting from (for example) differential trade costs; access advantage to urban economies (Fujita and Thisse, 2002). This empirical perspective provides insight and an approach towards understanding the role various IPM groups have on national nursery sales and how they are geographically dependent with each other.

However, the smooth transition model is more complex when local spillovers between nursery firms and regime splitting potential are admitted. For example, combining the STAR with the ARAR spatial process model suggests the following reduced form specification;

(4) $ARAR\text{-}STAR: \Delta y = A^{-1}Z\beta + A^{-1}G \cdot Z\delta + A^{-1}B^{-1}u \rightarrow \Delta y = \rho W \Delta y + Z\beta + G \cdot Z\delta + B^{-1}u.$

The hypotheses about spatial nonlinearity, lag, error, ARAR processes and their combinations (H_1 – H_8, listed below) were tested by calculating Wald statistics based on the robust covariance matrix This specification suggests the following hypotheses with respect to a baseline a-spatial that could be estimated using Ordinary Least Squares (OLS), and the usual spatial error (SEM) and spatial lag (SAR) process models:

(5)   H1: $\rho = 0, \lambda = 0, \delta = 0$ (a-spatial model, suggesting estimation with OLS),
(6)   H2: $\rho = 0, \lambda = 0, \delta \neq 0$ (STAR),
(7)   H3: $\rho = 0, \lambda \neq 0, \delta \neq 0$ (error process model with nonlinear parameters, SEM-STAR),

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(8)   H4: $\rho \neq 0, \lambda = 0, \delta \neq 0$ (lag process model with nonlinear parameters, SAR-STAR),

(9)   H5: $\rho \neq 0, \lambda \neq 0, \delta \neq 0$ (lag-error process model with nonlinear parameters, ARAR-STAR),

(10)   H6: $\rho \neq 0, \lambda \neq 0, \delta = 0$ (lag-error process model, ARAR),

(11)   H7: $\rho \neq 0, \lambda = 0, \delta = 0$ (spatial lag process model, SAR),

(12)   H8: $\rho = 0, \lambda \neq 0, \delta = 0$ (spatial error process model, SEM).

Estimation by General Method of Moments

Pede (2010) and Pede et al. (2010) outline the estimation of the spatial STAR models using maximum likelihood (ML). To relax the distributional assumption of normality maintained under ML, a general method of moments (GMM) estimator suggested by Kelejian and Prucha (2010) and Arraiz et.al. (2010) is proposed for the STAR versions of the SAR, SEM, and ARAR models.

Nonlinear least squares is used to estimate the basic a-spatial STAR model. Determining good starting values is critical for convergence. To calibrate the optimization procedure, a grid search over the shape and location parameters of each transition function with the objective of minimizing the concentrated sum of squared errors (SSE) is used,

(13) $SSE = \min_{r,c} \sum_{i=1}^{N}(y_i - \beta(\gamma, c; v)'Z_i)^2.$

Conditional on the shape and location parameters, the closed-form solution for the parameters is $\beta(\gamma, c; v) = (\tilde{Z}'\tilde{Z})^{-1}\tilde{Z}'y$, where $\tilde{Z} = [Z, GZ]$. Note that concentrating the objective in (13) reduces the problem of finding reasonable starting values to a grid search (Holt and Craig, 2006). The expected value of each $\gamma_i \geq 0$, so the outer grid domain ranged from 0 to 100 in increments of 0.5. The grid domain for each location parameter (c) was based on the 5th percentile of the transition variable distribution. The shape and location parameters that minimized the SSE objective were used as starting values in a nonlinear optimization routine to estimate the STAR and its spatial process variants.

For estimations of spatial process models, Anselin (2006) surveyed a variety of instruments that could be used to generate predicted values of the endogenous, spatially lagged dependent variable; $\widehat{Wy} = \tilde{P}Wy$ where $\tilde{P}$ is symmetric, positive definite, and idempotent projection matrix. Replacing Wy with its predicted value, the outcome variable is regressed on $\tilde{Z} = [Z, \widehat{Wy}]$, yielding the SAR-IV which is equal to the 2SLS estimator: $\delta_0 = (\tilde{Z}'\tilde{Z})^{-1}\tilde{Z}'y$. Standard errors for the estimator are adjusted for the "first stage" regression such that $AsyCov(\delta_0) =$ $\sigma_{IV}^2(\tilde{Z}'\tilde{Z})^{-1}$(assuming homoskedastic errors) with variance $\sigma_{IV}^2 = \frac{1}{n}\sum_{i=1}^{n}(y_i - \delta_0'Z_i)^2$, where Z includes the original data (Greene, 2000). A heteroskedastic-robust version could be estimated as,

(14) $\quad AsyCov(\delta)_{HET} = \left(\frac{n}{n-k}\right)(\tilde{Z}'\tilde{Z})^{-1}\tilde{Z}'\Omega\tilde{Z}(\tilde{Z}'\tilde{Z})^{-1},$

with Ω the diagonal matrix of the squared residuals, and the sample size divided by the degrees of freedom a small sample correction factor. Examples of IV's for Wy typically used in the applied literature include $Q_0 = [X, WX, W^2X]$ (e.g., Kelejian and Prucha, 1999). An alternative set of instruments, which is adopted here, includes Lee's (2003) "best" set of IV's, such that $Q_{BEST} = [X, W(I - \hat{\rho}_0W)^{-1}X\hat{\beta}_0]$, with $(\hat{\beta}_0, \hat{\rho}_0)$ obtained from a first round IV regression with instruments Q_0.

Modification of the SAR–IV to the SAR–STAR IV estimator is straightforward:

1. Replace Wy by its predicted value in the design matrix Z (as above).

2. Find good starting values of the shape (γ) and location (c) parameters of transition function, $G(\gamma, c; v)$ using a grid search.

3. Given reasonable starting values, use a constrained nonlinear optimization routine minimize the objective:

$$min_{(\gamma,c)}y'\left(I - Z_G(\tilde{Z}_G'\tilde{Z}_G)^{-1}\tilde{Z}_G'\right)y,$$

where $Z_G = [X, GX, Wy]$, and $\tilde{Z}_G = [X, GX, \widehat{Wy}]$.

4. Estimate standard errors using a heteroskedastic-robust covariance matrix (e.g., equation 14).

Similar steps may be applied to estimate the ARAR–STAR with the instruments defined above following Kelejian and Prucha (2010) (K&P) general moments procedure, with some minor modifications. For instance, an iterative procedure is applied to estimate a heteroskedastic–robust version of the error autoregressive parameter (λ). The algorithm used in this application to estimate that ARAR-STAR version follows:

1. Estimate the STAR model with double transitions, yielding G

2. Given G, construct a residual vector with the IV estimator based on Z_G and $\tilde{Z}_G$.

3. Find the error autoregressive parameter following K&P's procedure for estimating the ARAR process model with autoregressive and heteroskedastic disturbances.

4. Detrend the outcome and design matrix variables with the Cochran–Orcutt transformation as

$$y^* = y - \lambda Wy \text{ and } Z_G^* = Z_G - \lambda WZ_G.$$

5. Update the STAR parameters (γ, c) given (y^*, Z_G^*).

6. Return to step 1, and iterate until convergence (e.g., 0.000001, in this application).

Standard errors of the ARAR–STAR parameters are estimated using the asymptotic covariance matrix suggested by K&P (p. 60).

The step-wise iterative procedure used for the ARAR–STAR may be extended to cases where only error autocorrelation and spatial nonlinearities are considered, as in the case of the spatial error autoregressive model (SEM) with endogenous regimes (SEM–STAR). In this case, the IV matrix is an identity and Wy is omitted from the design matrix (Z). Standard errors may be estimated using an appropriate heteroskedastic–robust covariance matrix as above.

Results

Model Specification Results

In what follows, we discuss the econometric results on (1) model specification, (2) the spatial patterns of the transition function G, and (3) the total marginal effects of the predictors. Discussion centers on the covariates that were significantly correlated with nursery industry annual sales at the 5% significance level.

Using the Wald test, the null hypothesis of no spatial error correlation was rejected at 5% level (Table 3, Wald statistics=5.694). However, the null hypothesis that nursery industry annual sales in neighboring firms was uncorrelated with own-firm annual sales could not be rejected at 5% level (Wald statistics=1.536). Therefore, the model was estimated as a SEM–STAR model. The squared correlation coefficient was $r^2 = 0.77$, suggesting that about 77% of the variation in the data was explained by the model (Table 4). The transition function parameter was $\gamma = 3.2$ (shape parameter) and c=14.4% (the location parameter, in percentage). The relationship between predictors was nonlinear, suggesting sorting of firms into different regions.

STAR-SEM Model Results

On average, the effects of the covariates on nursery annual sales are gradually different moving past the 14.4% marker, which is the threshold of percent of total sales spent on advertising in 2008. The firms in the top percentile of the transition function G (i.e., firms with G = 1) are generally associated with firms spent more on advertising. Firms in the bottom part of the transition function (e.g., firms with G = 0) are associated with firms which spent less on advertising. There are a few firms appeared to be "in transition" with respect to nursery annual sales. Majority of the firms spend less than 14.4% of their total sales revenue on advertising. The spatial distribution of the transition "probabilities" generated by the G function was mapped (Figure 2).

In Table 4, the column titled "Regime 1" represents results for firms which spent less on advertising; while the coefficients in the column titled "Regime 2" are associated with firms which spent more on advertising. Discussion of the important covariates and associated heterogeneity follows two criterions. First, the main effect coefficients (the β's) had to be significant at the 5% level. Second, the coefficient associated with the transition function (the δ's) had to be significantly different from the reference coefficient at the 5% level. Significance of the δ's suggests that the relationship between a covariate and the total annual sales are heterogeneous across the space.

Keeping the rest of the explanatory variables constant, the importance of firm age was clearly separated into two regimes. For firms with less than 14.4% expenditures on advertising, a one year increase in firm age would multiply the nursery annual sales by exp (0.008)=1.008 times. While for firms with more than 14.4% expenditures on advertising, the relationship was a bit stronger, with the net marginal effect of firm age on nursery annual sales exp (0.008+0.038)=1.047 times. The number of trade shows firms attended also exhibited heterogeneity with respect to the nursery annual sales. For firms with low advertising expenditures, a 1%increase in trade show attended corresponded with a exp (-0.013)=0.987 times increase. As the firms advertising expenditures exceed 14.4% (that is, when G (AD; γ, c) = 1), firms moved to the upper tier of the regime, and the net marginal effect of tradeshow on annual sales became exp (-0.013+0.205)=1.212 times.

For firms with low expenditures on advertising, nursery industry annual sales in firms for which adopted IPM group of Mechanical Control (MC) was increased by exp (-0.858)=0.424 times , compared to not adopting MC. The relationship was nonlinear, with the association becoming much stronger beyond the 14.4% threshold. For firms with high expenditures on advertising, adopting the IPM group of Mechanical Control (MC) will increase the total sales by exp (-0.858+3.064)=9.079 times. It is interesting to note that the association between nursery annual sales and the adoption of

IPM group of Biological Control (BC) was significant for firms with low expenditures on advertising (Adoption of BC was correlated with a exp (-0.214)=0.807 times increase in total sales), but not for firms with high expenditures on advertising. Similar finding was found for predictors of Monitoring (M), Fertilization Rate (FR), and Preventive Practices (PP).

Conclusions

This exploratory analysis examined the relationship between IPM groups and national nursery industry sales. Nursery annual sales in 2008 were regressed on seven major Integrated Pest Management (IPM) groups controlling for selected production, management, and marketing practices. The hypothesis that the relationship between IPM groups on nursery sales was geographically heterogeneous was tested using a relatively new spatial econometric approach, a Smooth Transition Autoregressive (STAR) model. Evidence suggests the relationship between many of the predictors and the total sales was nonlinear across the region, and the association between certain groups and the nursery sales would be characterized into two distinct regimes. Estimation of the STAR model was extended to a nonlinear general method of moments approach. The procedure is flexible, and suggests a relatively straightforward approach towards model specification in terms of a "general-to-specific" search strategy.

Future research comparing estimation approaches applicable to the STAR process models will be useful to test findings in this study. While the advantages and disadvantages of ML and GMM estimation are well-know, the performance of the STAR model and its spatial process variants under different experimental parameters needs more investigation. Secondly, the performance of diagnostics used to specify STAR-class models should be investigated in a greater detail. In this application, a "general-to-specific" approach was taken to specify the regression model. How this specification search compares to a "specific-to-general" approach could provide information

regarding which types of tests should be used under different assumptions; e.g., Lagrange Multiplier tests, assuming a normal distribution compared to Wald tests in which the distributional assumptions are relaxed.

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Table 1: List of IPM Practices and Group Coding

IMP Practice Used	Percent of Respondents	Total Count	IPM Group
A. Remove infested plants	74.1%	2256	MC
D. Use cultivation, hand weeding	66.0%	2009	MC
N. Spot treatment with pesticides	62.3%	1897	PC
B. Alternate pesticides to avoid chemical resistance	51.5%	1567	PC
L. Inspect incoming stock	49.5%	1508	M
C. Elevate or space plants for air circulation	48.2%	1466	MC
O. Ventilate greenhouses	34.4%	1046	MC
J. Use mulches to suppress weeds	33.4%	1018	O
M. Manage irrigation to reduce pests	31.5%	960	WR
R. Adjust fertilization rates	31.0%	945	FR
I. Adjust pesticide application to protect beneficial insects	30.7%	934	PC
V. Use pest resistant varieties	29.9%	910	PP
E. Disinfect benches/ground cover	28.9%	880	O

K. Beneficial insect identification	24.1%	734	BC
H. Monitor pest population with tarp/sticky boards	20.8%	634	M
Q. Keep pest activity records	17.7%	540	PC
T. Use bio pesticides / lower toxicity	15.5%	473	PC
P. Use of beneficial insects	14.7%	447	BC
G. Soil solarization/sterilization	8.7%	265	O
S. Use screening/barriers to exclude pests	8.3%	253	MC
U. Treat retention pond water	3.8%	117	WR
F. Use sanitized water foot baths	2.2%	68	WR

Table 2: Variable Description and Summary Statistics

| Variable	Description	Mean	Std. Dev.
lnsales	log of annual sales in 2008	11.93	2.175
age	Firm age in terms of 2008	23.54	21.218
class	Firm size index based on annual sales (1-14)	2.366	2.4107
comscore	Computer technology usage	28.91	20.335
wholesale	Percent of 2008 sales to wholesale	49.94	42.738
tradeshow	Number of trade shows attended in 2008	1.382	4.058
AD	Percent of total sales spent on advertising in 2008	5.896	10.739
internet	Percent of advertising budget spent on internet websites	15.52	28.711
printed	Percent of advertising budget spent on printed materials	35.91	39.662
mass	Percent of advertising budget spent on mass media	16.4	29.302
MC	IPM group of Mechanical Control	0.941	0.236
PC	IPM group of Pesticide Control	0.862	0.346
WR	IPM group of Water Rate	0.399	0.49
M	IPM group of Monitoring	0.666	0.472
BC	IPM group of Biological Control	0.304	0.46
FR	IPM group of Fertilization Rate	0.366	0.482
PP	IPM group of Preventive Practices	0.382	0.486

Table 3: STAR-SEM Model Specification

Hypotheses	Wald Statistic	P-value
Spatial lag AR, H_0: $\rho = 0$	1.536	0.215
Spatial error AR, H_0: $\lambda = 0$	5.694	0.017
Joint lag/error, H_0: $\rho = \lambda = 0$	6.569	0.038
Spatial nonlinearity, H_0: $\delta = 0$	86.906	<0.0001
Joint nonlinearity/lag/error, H_0: $\delta = \rho = \lambda = 0$	92.819	<0.0001

Table 4: STAR-SEM Model Result

Variable Description	Regime 1		Regime 2	
	Coeff.	P-Value	Coeff.	P-Value
Intercept	10.026	0.000	-4.803	0.000
Firm age	0.008	0.000	0.038	0.009
Firm size	0.618	0.000	0.152	0.137
Computer tech. usage	0.007	0.003	-0.013	0.406
Marketing Practices				
Wholesale	0.006	0.000	-0.003	0.588
Tradeshow	-0.013	0.005	0.205	0.011
Internet	0.000	0.827	-0.011	0.190
Printed media	0.005	0.000	-0.001	0.846
Mass media	0.006	0.000	-0.006	0.461
IPM Practices				
Mechanical Control (MC)	-0.858	0.000	3.064	0.000
Pesticide Control (PC)	0.190	0.205	1.506	0.040
Water Rate (WR)	0.097	0.285	-0.409	0.293
Monitoring (M)	0.426	0.000	-0.659	0.145
Biological Control (BC)	-0.214	0.016	0.522	0.303
Fertilization Rate (FR)	0.195	0.040	-0.580	0.265
Preventive Practices (PP)	-0.190	0.043	0.017	0.974
Spatial Parameters and Model Fit				
λ	0.149	0.021		
γ	3.155	0.000		
c	14.411	0.000		
Sq. Corr.	0.770			

Figure 1: Example of the transition function and different levels of the smoothing parameter.
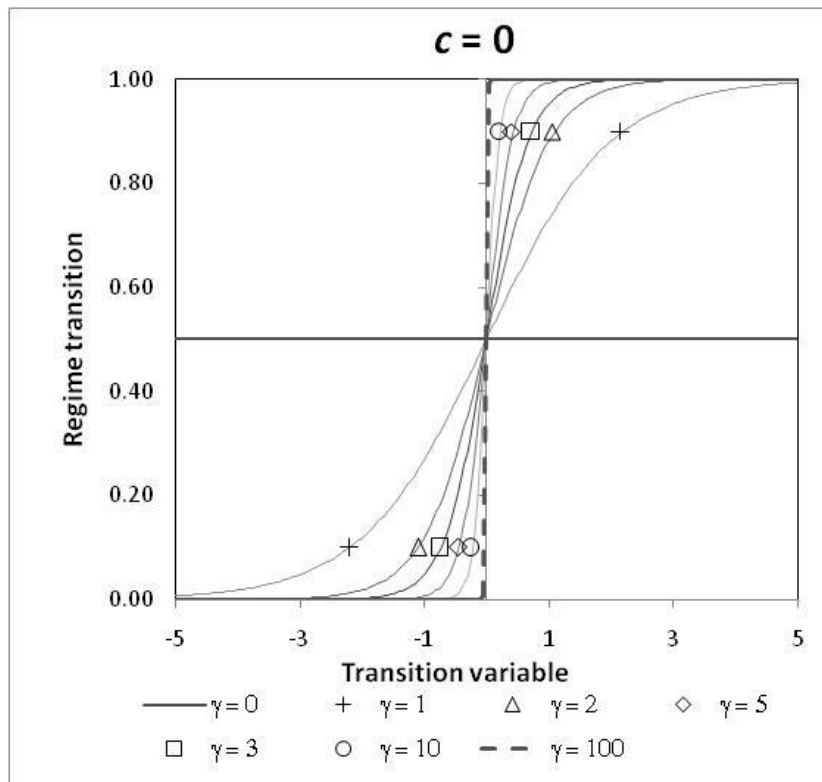
Comment: Note that two distinct regimes emerge when $\gamma = 100$, whereas there are no regimes identified when $\gamma = 0$. The parameter c functions as a location parameter; the inflection of the transition function is centered on c.

Figure 2: Transition function of the regime splitting variable