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for Spatial Spillover Effects in Dichotomous Choice
Contingent Valuation Surveys**

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A Spatial Probit Modeling Approach to Account for Spatial Spillover Effects in Dichotomous Choice Contingent Valuation Surveys

Introduction

Many contingent valuation method (CVM) studies apply the dichotomous-choice elicitation format as recommended by Arrow et al. (1993). The dichotomous-choice method involves sampling a large number of respondents asking if they would vote in favor or pay a particular randomly assigned dollar amount. Estimating Willingness to Pay WTP from a dichotomous-choice survey traditionally involves the use of Maximum Likelihood estimation techniques. Application of other estimation procedures is uncommon, and to date, few studies apply alternative methods (Halloway, Shankar and Rahman, 2002). While distance to a recreational amenity influences an individual's use value, few studies have examined how non-use or passive use values vary with distance. Yet, it is reasonable to believe that WTP will be similar for respondents living in the same region, particularly when the non-market good used for valuation has both use and non-use values. If observations of the dependent variable are similar to those in nearby locations, spatial dependence exists within the data, and standard probit models will result in biased estimated coefficients and therefore biased WTP estimates. Few studies applying spatial probit models exist in the context of estimating WTP. Recent advances in Bayesian estimation through application of Markov Chain Monte Carlo (MCMC) simulations and Gibbs sampling allow tractable estimation of spatial probit models that explicitly model spatial dependence and alleviate the possibility of biased estimated coefficients. In this paper, we present a demonstration of a Bayesian Spatial Probit model to investigate spatial spillover effects on WTP estimates.

Method

Bayesian estimation of a spatial probit involves repeated sampling using the Gibbs MCMC method. The spatial dependence in the probit model is represented as follows, where W is an $n \times n$ spatial weights matrix, ρ is the spatial autoregressive parameter, y is the observed value of the limited-dependent variable, y^* is the unobserved latent (net utility) dependent variable and X is a matrix of explanatory variables.

$$y = \begin{cases} 1 & \text{if } y^* > 0 \\ 0 & \text{if } y^* \leq 0 \end{cases}$$
$$y^* = (I_n - \rho W)^{-1} X\beta + \varepsilon$$
$$\varepsilon \sim N(0, I_n)$$

If ρ is not statistically significant, the spatial probit model collapses to the standard binary probit model. We estimate the general spatial model and relax the strict independence assumption used in standard probit models by allowing changes in one explanatory variable for one observation to impact the

values of other observations within a neighboring distance as defined by the spatial weights matrix, W . Intuitively, if the amount of the public good is increased for an individual observation, this will likely result in a decreased distance to the public good for that household *and* neighboring households, resulting in a marginal impact that goes beyond what is represented in a simple estimated coefficient. LeSage and Pace (2009) label the differing spatial impacts direct, indirect and total. In a standard probit, marginal impacts are measured by

$$\partial E[y|x_r]/\partial x_r = \varphi(\bar{x}_r\beta_r)\beta_r, \quad (1)$$

where x_r is the r th explanatory variable, \bar{x}_r is its mean, β_r is a standard probit estimate, and $\varphi(\cdot)$ is the standard normal density.

Marginal impacts in a spatial probit take spatial spillover effects into consideration and are no longer scalar. In a spatial probit,

$$\partial E[y|x_r]/\partial x'_r = \varphi(S^{-1}I_n\bar{x}_r\beta_r)\odot S^{-1}I_n\beta_r, \quad (2)$$

where $S = (I_n - \rho W)$ and I_n is an $n \times n$ identity matrix. In the spatial probit, the expected value of the dependent variable due to a change in x_r is now a function of the product of two matrices instead of two scalar parameters. The *direct* impact of changing x_r is represented by the main diagonal elements of (2), and the *total* impact of changing x_r is the average of the row sums of (2). Note that the *direct* impact is a function of ρ and W and is therefore different than the standard probit estimated coefficient. The *indirect* or spatial spillover effect is the *total* impact minus the *direct* impact.

Spatial Weights

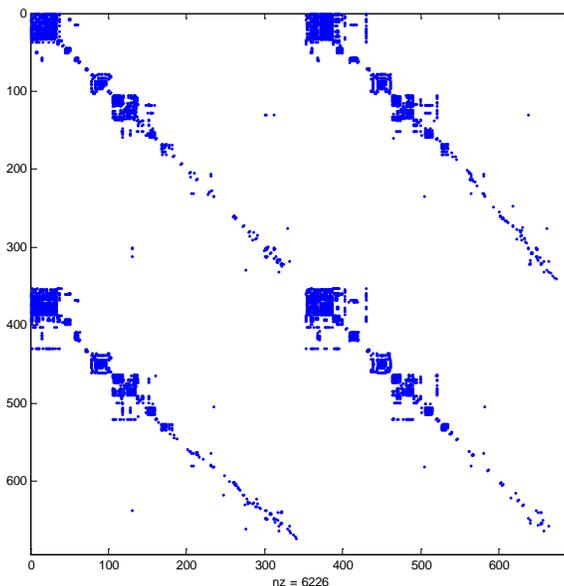
As seen in equations (1) – (2) correcting for spatial dependence involves the use of a spatial weights matrix. The weights matrix models the “neighbor” relationship within the observations of the dependent variables. We base our spatial weights matrix on distance from the zip code center to the center of the area where the public good, such as habitat, wetland or wilderness being preserved is located. W is an

$n \times n$ weights matrix of the form $W = \begin{bmatrix} 0 & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & 0 \end{bmatrix}$. Non-zero elements represent neighbors. Let d

represent the distance between two observations. We apply an inverse-distance weights matrix with non-zero elements $w_{ij} = \frac{1}{d^2}$ if $d_{i,j} < 10$ miles.¹ Therefore we have nonzero elements in the spatial weights matrix for all neighbors within 10 miles of each other. As shown in Figure 1, the sparse weights matrix has 6,226 non-zero elements.

¹MATLAB code was obtained from Donald LaCombe’s website: <http://www.rri.wvu.edu/lacombe/matlab.html> and used in conjunction with James LeSage’s MATLAB toolbox <http://www.spatial-econometrics.com/>

Figure 1: Spatial Weights Matrix



Willingness to Pay Estimates

The distribution of WTP is obtained using the parameter estimates from the standard probit. Following Hanneman (1984), WTP from a standard probit is

$$\frac{-\alpha}{\hat{\beta}_{Bid}} \quad (3)$$

Where

$$\alpha = \hat{\beta}_0 + (\hat{\beta}_1 \times \bar{X}_1) + (\hat{\beta}_2 \times \bar{X}_2) + \dots + (\hat{\beta}_{K-1} \times \bar{X}_{K-1}) \quad (4)$$

for all the explanatory variables except for $\hat{\beta}_{Bid}$

Thus, WTP is a function of independent variables. Because we are taking into account spatial dependencies among the independent variables, we use *total impacts* instead of estimated coefficients on the explanatory variables in our WTP function. Thus we obtain WTP taking into account the total impacts and the WTP from the spatial probit substituting $\hat{\beta}$'s with \hat{T} from equation (3) where \hat{T} is the *total impact* of the given explanatory variable. Therefore,

$$\alpha = \hat{\beta}_0 + (\hat{T}_1 \times \bar{X}_1) + (\hat{T}_2 \times \bar{X}_2) + \dots + (\hat{T}_{K-1} \times \bar{X}_{K-1}) \quad (5)$$

for all the explanatory variables except for $\hat{\beta}_{Bid}$.

Hypothesis Tests

If spatial dependence exists within our data, our coefficient estimates will be biased, leading to biased WTP estimates. Therefore, we test the following hypothesis:

$$H_0: \rho=0 \quad (6)$$

$$H_A: \rho \neq 0$$

If $\rho \neq 0$, then we conclude that spatial dependence exists within our data, and that our estimated coefficients in the standard probit are biased.

In addition to testing for spatial dependence, we want to test to see if the WTP estimates from the standard probit are different than the WTP estimates from the spatial probit. Therefore, we test the following hypothesis:

$$H_0: WTP_{\text{Non-Spatial Probit}} = WTP_{\text{Spatial Probit}} \quad (7)$$

$$H_A: WTP_{\text{Non-Spatial Probit}} \neq WTP_{\text{Spatial Probit}}$$

We use the complete combinatorial method described in Poe, Giraud, and Loomis (2005) to test for differences in WTP. To apply the complete combinatorial method, we randomly sample 1,000 positive draws from each WTP distribution. The complete combinatorial method calculates the difference between each element of each WTP vector, resulting in a vector of 1,000,000 differences. The proportion of non-positive values of the difference vector is equal to $\hat{\gamma}$. $\hat{\gamma}$ corresponds to the p-value of the null hypothesis in equation (7). If we reject the null hypothesis in (7), we conclude that the bias in the estimated coefficients has economic significance and that WTP from a spatial probit is statistically different from WTP in a non-spatial probit.

Data

Our case study to demonstrate the spatial probit model involves protection of Spotted Owl habitats in the Four Corners area of the USA which includes Utah, Colorado, Arizona, and New Mexico. Preservation of a species and its habitat have values beyond the species preservation through recreation and use, thus it is reasonable to believe that people living closer to the habitat may have a higher WTP for preservation. Mexican Spotted Owls are found in the Southwestern United States and Mexico. In the early nineties, it was recognized that without habitat protection the Mexican Spotted Owl would be extinct within 15 years. Therefore, the Mexican Spotted Owl was added to the list of Endangered Species in 1993.² The spotted owl requires old growth forests for its habitat, and the designation of forests as protected areas has sparked a controversial debate in the Southwest region of the U.S. about the benefits and costs of endangered species habitat recovery. The data are from a survey of U.S. residents for WTP to preserve habitat for the Mexican Spotted Owl. See Loomis and Elkstrand (1998) for a detailed description of the data. In addition to the typical questions for a contingent valuation survey, information was obtained using GIS about the distance from the respondents' residence to the nearest Mexican Spotted Owl habitat.

² <http://ecos.fws.gov/speciesProfile/profile/speciesProfile.action?sPCODE=B074>

We estimate WTP as a function of:

- Bid amount
- Distance to nearest critical habitat
- Importance to the respondent of jobs
- Importance to the respondent of environmental protection.

Therefore, for the standard probit,

$$\alpha = \hat{\beta}_0 + (\hat{\beta}_{Pro-job} \times \bar{X}_{Pro-job}) + (\hat{\beta}_{Protect} \times \bar{X}_{Protect}) + (\hat{\beta}_{Distance} \times \bar{X}_{Distance}) \quad (8)$$

where the $\hat{\beta}$'s are obtained from standard probit estimation. We obtain 9,000 draws of WTP using the Krinsky Robb (1986) approach discussed in Park, Loomis and Creel (1991). The Krinsky Robb method can be used to simulate a distribution for any nonlinear function of estimated parameters, and is commonly applied to estimates of WTP from dichotomous-choice contingent valuation studies.

For the spatial probit,

$$\alpha = \hat{\beta}_0 + (\hat{T}_{Pro-job} \times \bar{X}_{Pro-job}) + (\hat{T}_{Protect} \times \bar{X}_{Protect}) + (\hat{T}_{Distance} \times \bar{X}_{Distance}). \quad (9)$$

where the total impacts are obtained from the average of the row sums of the marginal effects matrix in equation (2) and the $\hat{\beta}$'s are the estimated coefficients from the spatial probit. We obtain 9,000 draws of total impacts and of $\hat{\beta}_0$ and $\hat{\beta}_{Bid}$ from the Gibbs sampling of the Bayesian estimation.

Results

Both standard ML and Bayesian spatial probit models are estimated. The results are presented in Table 1. The spatial autoregressive parameter shows the Bayesian equivalence of statistical significance in the spatial probit, thus we reject the null hypothesis in equation (6) in favor of the spatial model.³ The statistically significant ρ indicates that the estimated coefficients in the non-spatial probit are biased, and may lead to incorrect estimates of WTP. Per household WTP values are \$52.56 in the standard probit and \$65.99 in the spatial probit. To test whether the WTP estimates are statistically different, we use the Krinsky-Robb (1986) procedure to estimate 9,000 draws for WTP from the non-spatial probit, and we use a random sample of the positive post-estimation draws for estimated coefficients to find WTP from the non-spatial models.⁴

³ The "p-values" are calculated using the method described in Gelman et al. (1995).

⁴ Jeanty, P. Wilner. 2007. "wtpcikr: Constructing Krinsky and Robb Confidence Interval for Mean and Median Willingness to Pay (WTP) Using Stata." North American Stata Users' Group Meetings 2007, 8.

Table 1: Probit Estimation Results for Spatial and Non-spatial Models with Estimates of WTP

<i>Variable</i>	Non-spatial		Spatial		<i>Total Impacts</i>
	<i>Coefficient</i>	<i>p-value</i>	<i>Coefficient</i>	<i>p-value</i>	
Constant	-0.00519	<0.0001	0.21826	0.2158	
Owl Bid Amount	-0.00009	0.3170	-0.00522	<0.0001	
Distance in Miles	-0.20455	<0.0001	-0.00009	0.1603	-0.00002
Pro-job	0.12585	<0.0001	-0.20526	<0.0001	-0.05398
Protect	0.20116	0.4760	0.12785	<0.0001	0.03362
ρ			-0.08500	<0.0001	
N (Sample Size)	676		676		
WTP	\$52.56		\$65.99		

We apply the complete combinatorial method and obtain a $\hat{\gamma} = 0.33$. The $\hat{\gamma}$ from complete combinatorial is analogous to the p-value in traditional hypothesis testing. The decision rule using the complete combinatorial method is to reject the null hypothesis of a mean difference of zero if $\hat{\gamma}$ is less than the level of significance. Therefore, we fail to reject the null hypothesis in equation (7) and conclude we do not have sufficient statistical evidence to show a difference in the empirical distributions of WTP. The lack of significant difference in the face of rather large absolute difference in the biased estimate of WTP from the non-spatial probit may be due to the large variance in the estimate of WTP from the spatial probit because we have included direct and indirect impacts in our WTP calculation.

Conclusions

WTP estimates from Dichotomous-Choice Contingent Valuation surveys are used to inform environmental policies. Many DC-CV surveys estimate values of non-market goods where WTP is likely to depend upon distance. If spatial dependence exists within the DC-CV data, estimates of WTP obtained from standard probit estimated coefficients are biased. In this paper we test for spatial effects using a Bayesian spatial probit dichotomous choice contingent valuation Model, and find such spatial effects to be statistically significant. Thus WTP estimates from the non-spatial probit model are biased. While we find economically different values of WTP, when we apply the complete combinatorial method to compare distributions of WTP, we fail to reject the null hypothesis of statistical difference between the mean WTP estimates. Although we cannot conclude the means of WTP are different, the mean value of WTP from the spatial model is \$13.43 higher than the mean WTP from the standard probit. Given the large actual differences in estimated WTP, we recommend that explicit spatial modeling be used to test for spatial dependence because spatial dependence can result in biased benefit estimates using non-spatial model with potentially important ramifications for policy analyses. However, to assess whether spatial

dependence in dichotomous choice contingent valuation is frequently encountered and whether it results in policy relevant differences in WTP requires more empirical testing using a wide variety of public goods.

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