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

John B. Loomis and Julie M. Mueller

We present a demonstration of a Bayesian spatial probit model for a dichotomous choice contingent valuation method willingness-to-pay (WTP) questions. If voting behavior is spatially correlated, spatial interdependence exists within the data, and standard probit models will result in biased and inconsistent estimated nonbid coefficients. Adjusting sample WTP to population WTP requires unbiased estimates of the nonbid coefficients, and we find a \$17 difference in population WTP per household in a standard vs. spatial model. We conclude that failure to correctly model spatial dependence can lead to differences in WTP estimates with potentially important policy ramifications.

Key Words: Bayesian estimation, contingent valuation, spatial probit, willingness to pay

JEL Classifications: C11, Q51

Distance to an environmental amenity influences an individual's use value, yet few studies have examined how nonuse or passive use values vary with distance. Many contingent valuation method (CV) studies apply the dichotomous-choice elicitation format as recommended by Carson et al. (2003) to value environmental amenities. The dichotomous-choice CV method involves sampling a large number of respondents asking if they would

vote in favor of a referenda and 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. In this article, we extend the methodology of estimating WTP from dichotomous-choice CV survey data by explicitly modeling for spatial dependence using Bayesian estimation techniques. We also examine the impact of explicit spatial modeling on policy-relevant WTP estimates.

It is reasonable to believe that WTP per household will share some similarities among respondents living in the same region, particularly when the nonmarket good used for valuation has both use and nonuse values. If observations of the dependent variable are similar to those in nearby locations, spatial interdependence exists within the data, and standard models will result in biased and

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inefficient estimated nonbid coefficients such as attitudes and demographics. As outlined in Franzese, Hays, and Schaffer (2010), voting behavior is shown to be correlated across space in the political science literature. Most dichotomous-choice CV surveys follow the traditional method of referendum format. Thus, the survey proposes a hypothetical vote. Therefore, spatial dependence will likely exist in the data if a respondent's propensity to vote "yes" is related to his/her neighbor's response. Although many past CV studies control for distance to the natural environment being protected and include respondents' attitudes about protecting the environment, heterogeneity related to location is likely to exist in voting-type data. If the spatial heterogeneity exists to an extent not controlled for by explanatory variables, all of the estimated nonbid coefficients are biased.

Commonly estimated standard probit models assume spatial independence of the observations. To quote Franzese, Hays, and Schaffer (2010), "working under the incorrect assumption of spatial interdependence...threatens over-confidence or inefficiency in the best of circumstances, and usually bias and inconsistency as well." Franzese, Hays, and Schaffer refer to problems in the estimated coefficients of a standard probit in the face of spatial heterogeneity. WTP calculations are obtained from the estimated coefficients from probit models and sample means from relevant explanatory variables. Sample representativeness corrections can be made to ensure that the predicted WTP represents the population, even if the sample is not perfectly representative (Loomis, 1987). However, these corrections require unbiased and consistent estimates of the nonbid probit coefficients. If probit coefficients are biased, population projections used for decision-making will be based on biased estimates of WTP.

We investigate potential differences in WTP from spatial spillovers using data involving protection of Mexican Spotted Owl habitats. Mexican Spotted Owls are found in the southwestern United States and Mexico. In the early 1990s, it was recognized that without habitat protection, the Mexican Spotted Owl would be

extinct within 15 years.¹ Therefore, the Mexican Spotted Owl was added to the list of endangered species in 1993. Because the Mexican Spotted Owl requires old growth forests for its habitat, the designation of forests as protected areas has sparked a controversial debate in the southwest region of the United States about the benefits and costs of endangered species habitat recovery. Protection of the species and its habitat may have use values through potential recreational use of the old growth forest habitat. Thus, it is reasonable to believe that people living closer to the habitat may have a higher WTP for preservation. In addition, people throughout the United States may also hold nonuse values for the continued existence of a self-sustaining population of Mexican Spotted Owls (see Richardson and Loomis, 2009, for a summary of endangered species values). Prior studies of the California and Northern spotted owls in California and Oregon have documented values of these two spotted owl species (Loomis and Gonzalez-Caban, 2010). Loomis (2000) found that although people who live more than 1000 miles away from the owl's habitat still have significant values per household, values are substantially higher in the two states that contain the species' habitat. Although the previous spotted owl studies investigate the potential impact of distance on WTP for habitat protection, none explicitly model for spatial dependence. Policy decisions incorporate results from probit models, and if the models contain biased estimated coefficients, failure of previous studies to explicitly model for spatial dependence may result in policy-relevant differences in estimated WTP.

Spatial probit models have been estimated using full-information maximum likelihood (McMillen, 1992; Murdoch, Sandler, and Vijverberg, 2003), weighted least squares (McMillen, 1992), and generalized method of moments estimators (Pinkse and Slade, 1998). Classical methods, especially use of maximum likelihood techniques, can require hours to

¹For more information on the Spotted Owl endangered species profile, visit <http://ecos.fws.gov/speciesProfile/profile/speciesProfile.action?spcode=B074>.

estimate small sample problems (LeSage and Pace, 2009). In addition, with classical or nonsampling type estimation procedures, simulation is necessary postestimation to obtain a distribution of WTP. In contrast, Bayesian estimation with Markov Chain Monte Carlo (MCMC) simulations and Gibbs sampling provides distributions of the draws of WTP postestimation without further simulation. We choose the Bayesian methodology for our spatial probit model for its relative computational ease in estimation and because Bayesian methods provide postestimation draws for parameters that are easily computed into draws for WTP.

Other authors estimate WTP from standard probit models using Bayesian methods, including Li et al. (2009) and Yoo (2004). In addition, Holloway, Shankar, and Rahman (2002) used Bayesian methods to estimate spatial probit models. Although other authors estimate WTP from standard probit models using Bayesian methods, and Bayesian spatial probit models have been estimated in other contexts, we are unaware of the use of any type of spatial probit model applied in the context of estimating WTP from dichotomous-choice CV data. In this article, we present what is, to the authors' knowledge, the first application of a spatial probit model to investigate spatial spillover effects on WTP estimates.

Method

Bayesian estimation of a spatial probit involves repeated sampling using the MCMC method and Gibbs sampling. The spatial interdependence in the probit model is represented as follows, where \mathbf{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.

$$(1) \quad y = \begin{cases} 1 & \text{if } y^* > 0 \\ 0 & \text{if } y^* \leq 0 \end{cases}$$

$$(2) \quad y^* = (\mathbf{I}_n - \rho \mathbf{W})^{-1} \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

$$(3) \quad \boldsymbol{\varepsilon} \sim N(0, \mathbf{I}_n)$$

If $\rho = 0$, the spatial probit model collapses to the standard binary probit model. We estimate

the general spatial model and relax the strict interdependence 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, \mathbf{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. To see the role of direct, indirect, and total effects, we compare the marginal effects of the standard probit with that of the spatial probit. In a standard probit, marginal impacts are measured by:

$$(4) \quad \frac{\partial E[y|x_r]}{\partial x_r} = \varphi(\bar{x}_r \boldsymbol{\beta}_r) \boldsymbol{\beta}_r,$$

where x_r is the r th explanatory variable, \bar{x}_r is its mean, $\boldsymbol{\beta}_r$ 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,

$$(5) \quad \frac{\partial E[y|x_r]}{\partial x_r} = \varphi(\mathbf{S}^{-1} \mathbf{I}_n \bar{x}_r \boldsymbol{\beta}_r) \mathbf{O} \mathbf{S}^{-1} \mathbf{I}_n \boldsymbol{\beta}_r,$$

where $\mathbf{S} = (\mathbf{I}_n - \rho \mathbf{W})$ and \mathbf{I}_n is an $n \times n$ identity matrix. In the spatial probit, the expected value of the dependent variable resulting from 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 (Equation 5), and the total impact of changing x_r is the average of the row sums of (Equation 5). Note that the direct impact is a function of ρ and \mathbf{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, modeling spatial interdependence involves the use of a spatial weights matrix. All spatial spillover and feedback effects work through the spatial weights matrix. Unlike including a distance variable as an explanatory variable, which models the distance from an observation to the habitat or environmental amenity under analysis, the spatial weight matrix models the neighbor relationship between observations. We base our spatial weights matrix on distances between observations. \mathbf{W} is an $n \times n$ weights matrix of

the form $\mathbf{W} = \begin{bmatrix} \mathbf{0} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & \mathbf{0} \end{bmatrix}$. Nonzero

elements represent neighbors. Let d represent the distance between two observations. We apply an inverse-distance weights matrix with nonzero elements $w_{ij} = \frac{1}{d^2}$ if $d_{ij} < 10$ miles.² Therefore, we have nonzero elements in the spatial weights matrix for all neighbors within 10 miles of each other. We believe 10 miles represents a reasonable distance for the neighbor relationship within our national data set. Although other weight specifications exist, in any spatial econometric problem, the choice of the weights is exogenous and determined by the researcher (Mueller and Loomis, 2010). Investigation of the impact of choice of spatial weight matrices is a valuable area of potential research in spatial probit models.

Willingness-to-Pay Estimates

For a standard probit model, following Hanneman (1984), WTP is a function of α , a “grand constant,” and the coefficient on the bid amount. In the standard probit,

$$(6) \quad \alpha = (\hat{\beta}_1 \times \bar{X}_1) + (\hat{\beta}_2 \times \bar{X}_2) + \cdots + (\hat{\beta}_{K-1} \times \bar{X}_{K-1})$$

for all the explanatory variables except for $\hat{\beta}_{Bid}$. Thus, WTP is a function of independent variables.

In the spatial probit model, 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. 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 6 where \hat{T} is the total impact of the given explanatory variable. Therefore,

$$(7) \quad \alpha = (\hat{T}_1 \times \bar{X}_1) + (\hat{T}_2 \times \bar{X}_2) + \cdots + (\hat{T}_{K-1} \times \bar{X}_{K-1})$$

for all the explanatory variables except for $\hat{\beta}_{Bid}$. The total impacts will be a function of the spatial weights matrix and the estimated spatial autoregressive parameter ρ . Intuitively, in the spatial probit model, a change in the value of an explanatory variable for one observation will have an impact on that observation and its neighbors. In turn, the change in the value for the neighbors will have a feedback effect on the observation. Marginal effects in a spatial probit model are not one-dimensional, and direct comparison of estimated coefficients across models does not take into account any spatial feedback effects. We take into account these feedback or spatial spillover effects from the spatial probit in our WTP estimates by using total impacts to obtain WTP.

Hypothesis Tests for Spatial Effects

The focus of our analysis is the impact of spatial interdependence on WTP estimates. Although some studies may focus on the impacts of modeling on point estimates, we note that WTP estimates are obtained from combinations of estimated coefficients. In studies determining WTP values, the focus is on the effects or measured impacts of the explanatory variables, not necessarily a single point estimate.

First, we want to determine if spatial interdependence exists within our data. If spatial interdependence exists within our data, our nonbid coefficient estimates will be biased,

²MATLAB code was obtained from Donald Lacombe's web site: www.rrri.wvu.edu/lacombe/matlab.html and used in conjunction with James LeSage's MATLAB toolbox: www.spatial-econometrics.com/.

leading to biased WTP estimates. Therefore, we test the following hypothesis regarding the spatial autoregressive parameter:

$$(8) \quad \begin{aligned} H_0: \rho &= 0 \\ H_A: \rho &\neq 0 \end{aligned}$$

If $\rho \neq 0$, then we conclude that our estimated nonbid coefficients in the standard probit are biased.

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

$$(9) \quad \begin{aligned} H_0: \text{WTP}_{\text{Non-Spatial Probit}} &= \text{WTP}_{\text{Spatial Probit}} \\ H_A: \text{WTP}_{\text{Non-Spatial Probit}} &\neq \text{WTP}_{\text{Spatial Probit}} \end{aligned}$$

We use the complete combinatorial method described in Poe, Giraud, and Loomis (2005) to test for differences in WTP. The complete combinatorial method calculates the difference between each element of each WTP vector, resulting in a vector of differences. The proportion of nonpositive values of the difference vector is equal to $\hat{\gamma}$. $\hat{\gamma}$ corresponds to the p value of the null hypothesis in Equation 9. If we reject the null hypothesis in Equation 9, then WTP from a spatial probit is statistically different from WTP in a non-spatial probit.

Data

The data are from a mail survey of U.S. residents for WTP to preserve the habitat for the Mexican Spotted Owl. The Dillman (2000) Tailored Design Method including repeat mailing approach was followed. Our first mailing involved 1600 surveys. After deleting undeliverables, the response rate was 54.4% or 734 respondents, leaving 684 complete observations for our spatial specification.

The 12-page survey plus map insert underwent the scrutiny of four focus groups and a pretest. Each survey contained detailed maps showing the location of the critical habitat units in Arizona, Colorado, New Mexico, and Utah that form the Four Corners Region along with

a description of the current recovery effort. The description was followed by a proposal to reduce the protection for the threatened Mexican Spotted Owl to allow for increased economic activity and reduce federal management expenditures. The survey then proposed a Mexican Spotted Owl Recovery Trust Fund to continue the current recovery program. Households were told if they agreed to pay, the program would continue with the likelihood the Mexican Spotted Owl would recover in 15 years and could be delisted. They also were told if they did not pay, then it was likely the Mexican Spotted Owl would become extinct in 15 years. The wording of the WTP question was: If the Mexican Spotted Owl Recovery Trust Fund was the only issue on the next ballot and it cost your household \$YY every year, would you vote in favor of it?

The \$YY was replaced by 14 bid amounts ranged from \$1 to \$350. The bid amounts used are \$1, 3, 5, 10, 15, 20, 30, 40, 50, 75, 100, 150, 200, and 350.

In addition, typical questions for a contingent valuation survey including Likert scale attitude questions about environmental protection were asked. Information about the distance from the respondents' residence to the nearest Mexican Spotted Owl habitat and to other households was obtained using GIS.

Econometric Specification

Based on past literature, we included several independent variables. Loomis (2000) found distance from the habitat to be protected was frequently a significant variable in explaining WTP. Table 1 provides descriptions and summary statistics for relevant variables.

The Protect and Pro-job variables were found to be statistically significant in past simple nonspatial analyses of the Mexican Spotted Owl CV data (see Giraud, Loomis, and Johnson, 1999). Education is often found to be a statistically significant variable in CV WTP studies (Loomis, 1987). Therefore, we specify WTP as a function of bid amount and the following explanatory variables:

Table 1. Summary Statistics and Variable Definitions

Variable	Mean	Standard Deviation
<i>Log of bid amount</i>		
The natural log of a randomly assigned bid amount, where actual bids were randomly assigned from the following: \$1, 3, 5, 10, 15, 20, 30, 40, 50, 75, 100, 150, 200, 350	3.39	1.57
<i>Miles</i>		
Distance from nearest critical habitat (miles)	560	603
<i>Miles squared</i>		
Distance from nearest critical habitat squared (miles)	634,931	968,234
<i>Pro-job</i>		
Measure of the importance of using public lands for commercial uses and jobs, measured as a sum of the following two 5-point Likert scale items: <ul style="list-style-type: none">• Businesses should be allowed to extract natural resources from Federal lands• If any jobs are lost, the cost of protecting threatened and endangered species is too large	6.62	2.10
<i>Protect</i>		
Measure of the importance of protecting threatened and endangered species, measured as a sum of the following three 5-point Likert scale items: <ul style="list-style-type: none">• All threatened and endangered species should be protected• I am glad threatened and endangered species are protected in the Four Corners area even if I never see them• Protection of threatened and endangered species is a responsibility I am willing to pay for	9.86	4.38
<i>Education</i>		
Maximum number of years of education completed	14.79	2.98
<i>Western Region</i>		
A dummy variable equal to 1 if the respondent lives in one of the following Western states: Arizona, New Mexico, Colorado, Utah Nevada, Idaho, and Wyoming	0.56	0.50

- Distance in miles to the nearest critical habitat;
- Distance in miles squared;
- Importance to the respondent of jobs (Pro-job);
- Importance to the respondent of environmental protection (Protect);
- Education (years); and
- Western region indicator variable.

We include both distance in miles and distance squared to allow nonlinearity in the distance relationship. Whether a respondent places high importance on protecting jobs or the environment is also likely to influence his/her

WTP to protect the Mexican Spotted Owl habitat, and therefore we include both Pro-job and Protect as explanatory variables. We include the highest number of years of education attained in each household as a demographic variable. We also include a western regional dummy variable to act as a proxy for any other spatial fixed effects not included in other explanatory variables. The variable western region is equal to one for the intermountain Western states, including the Four Corner States where the prime habitat is Arizona, New Mexico, Colorado, Utah and states adjacent to them, Nevada, Idaho, and Wyoming. We

believe including this regional variable will control for differences in preferences for habitat protection because the majority of the Mexican Spotted Owl habitat exists in these states. We use the same explanatory variables, \mathbf{X} , in the standard probit and the spatial probit models.

Spatial Probit Model

We estimate the spatial probit model using Bayesian estimation and Gibbs sampling (Gelfand et al., 1990). Following Li et al. (2009), let WTP represent a latent variable on n observations. WTP for an individual is then a function of the explanatory variables, \mathbf{X} , and the other parameters of interest $\boldsymbol{\beta}$ and σ . β_0 and s_0 are the initial values of the parameters of interest, N denotes the normal distribution and IG denotes the inverse gamma distribution. Thus,

$$(10) \quad WTP^* \sim N(\mathbf{X}'\boldsymbol{\beta}, \sigma^2)$$

and $\boldsymbol{\beta}$ and σ are independent with

$$(11) \quad \boldsymbol{\beta} | \sigma^2 \sim N(\beta_0, \sigma^2 \beta_0^{(-1)})$$

and

$$(12) \quad \sigma^2 \sim IG(\gamma_0/2, \gamma_0 s_0^2/2).$$

$$(16) \quad \alpha_{\text{Standard}} = (\hat{\beta}_{\text{Distance}} \times \bar{X}_{\text{Distance}}) + (\hat{\beta}_{\text{DistanceSquared}} \times \bar{X}_{\text{DistanceSquared}}) + (\hat{\beta}_{\text{Pro-job}} \times \bar{X}_{\text{Pro-job}}) \\ + (\hat{\beta}_{\text{Protect}} \times \bar{X}_{\text{Protect}}) + (\hat{\beta}_{\text{Education}} \times \bar{X}_{\text{Education}}) + (\hat{\beta}_{\text{West}} \times \bar{X}_{\text{West}}),$$

The Gibbs sampler starts with initial values (in our case, the initial values are set = 0) and draws $\boldsymbol{\beta}$ and σ through simulations. The spatial probit model leads to a multivariate truncated normal distribution for the latent y^* parameters. Following LeSage and Pace (2009),

$$(13) \quad WTP^* | \boldsymbol{\beta}, \rho \sim \text{TMVN} \\ \times \left\{ (\mathbf{I}_n - \rho \mathbf{W})^{(-1)} \mathbf{X} \boldsymbol{\beta} [(\mathbf{I}_n - \rho \mathbf{W})' (\mathbf{I}_n - \rho \mathbf{W})]^{(-1)} \right\}$$

Now, unlike the standard probit, the latent WTP is thus distributed:

$$(14) \quad \boldsymbol{\beta} | \rho, WTP^* \sim N(c^*, \mathbf{T}^*) \\ c^* = (\mathbf{X}'\mathbf{X} + \mathbf{T}^{-1})^{-1} (\mathbf{X}'\mathbf{S}y^* + \mathbf{T}^{-1}c) \\ \mathbf{T}^* = (\mathbf{X}'\mathbf{X} + \mathbf{T}^{-1})^{-1} \\ \mathbf{S} = (\mathbf{I}_n - \rho \mathbf{W}).$$

We also need to sample for ρ using the Metropolis Hastings approach. For the approach,

$$(15) \quad \rho | \boldsymbol{\beta}, WTP^* \sim |\mathbf{I}_n - \rho \mathbf{W}| \exp \\ \times \left(-1/2 [\mathbf{S}y^* - \mathbf{X}\boldsymbol{\beta}]' [\mathbf{S}y^* - \mathbf{X}\boldsymbol{\beta}] \right).$$

We make 10,000 passes through $WTP^* | \boldsymbol{\beta}, \rho$, $\boldsymbol{\beta} | \rho, WTP^*$, and $\rho | \boldsymbol{\beta}, WTP^*$. We use Gibbs sampling for $WTP^* | \boldsymbol{\beta}, \rho$, $\boldsymbol{\beta} | \rho, WTP^*$, and Metropolis Hastings for $\rho | \boldsymbol{\beta}, WTP^*$. We omit the initial 9000 simulations for burn-in and keep the last 1000 draws to calculate WTP.

Calculation of Willingness to Pay

We use maximum likelihood estimation to obtain parameter estimates for the standard probit model. We then use the Krinsky and Robb (1986) method to simulate 1000 draws of the WTP function. For the standard probit:

where the $\hat{\beta}$ s are vectors of draws obtained from the Bayesian estimation. WTP is obtained by dividing α_{Standard} by $\hat{\beta}_{\text{Bid}}$.

For the spatial probit, because we use MCMC methods to estimate WTP, we do not have to use additional simulation procedures to estimate WTP from the regression coefficients. We obtain 1000 draws of WTP as a function of the draws from the distribution of the estimated parameters. We include total effects in our WTP estimates from the spatial probit. Thus:

(17)
$$\alpha_{Spatial} = (\hat{T}_{Distance} \times \bar{X}_{Distance}) + (\hat{T}_{Distance\ Squared} \times \bar{X}_{Distance\ Squared}) + (\hat{T}_{Pro-job} \times \bar{X}_{Pro-job}) + (\hat{T}_{Protect} \times \bar{X}_{Protect}) + (\hat{T}_{Education} \times \bar{X}_{Education}) + (\hat{T}_{West} \times \bar{X}_{West}),$$

where \hat{T} , the total impacts, are vectors of draws obtained from the average of the row sums of the marginal effects matrix in Equation 5. We use log of bid amount in the spatial probit and WTP is obtained by the following transformation (Hanneman, 1984):

(18)
$$e^{-\alpha/\hat{\beta}_{Bid}} \frac{\pi/\hat{\beta}_{Bid}}{\sin \pi/\hat{\beta}_{Bid}}.$$

Results and Analysis

The standard probit results are presented in Table 2, and the Bayesian spatial probit results are presented in Table 3. Both models have p values < 0.0001 for the estimated coefficients on bid amount. For the spatial probit, the p values are calculated using the method described in Gelman et al. (1995). The estimated coefficients on bid amount in both models are negative, indicating that propensity to vote “yes” decreases as the randomly assigned bid amount increases.

Table 2. Standard Probit Model Results

Variable	Coefficient	p Value
Bid amount	−0.005182	<0.0001
Distance in miles	0.000196	0.7280
Distance squared	0.000000	0.7310
Pro-job	−0.197959	<0.0001
Protect	0.126760	<0.0001
Education	0.039302	0.0390
Western region	0.191741	0.4810
Constant	−0.509555	0.3110
Mean WTP sample		\$54.62
95% CI		[\$33.09–\$72.12]
Mean WTP population		\$37.65
95% CI		[\$−10.61 to \$75.71]

WTP, willingness to pay; CI, confidence interval.

Both models have insignificant p values on the estimated coefficient on distance in miles and distance in miles squared. The lack of predictive power on the distance coefficients in both models is noteworthy. Many researchers defend the use of the standard probit model in the face of possible spatial interdependence using an omitted variables defense—claiming that if researchers are careful in their choice of independent variables, spatial interdependencies will be taken into account. However, even with distance being insignificant, if spatial dependence exists in the error terms of the standard probit, this can lead to heteroscedasticity and inconsistent estimates in the standard probit model (Pinkse and Slade, 2010).

Our empirical results seem to weaken the omitted variables defense. The nature of the Mexican Spotted Owl habitat is unique in that the owls necessitate an old growth forest habitat. Old growth forest may provide other amenities for respondents besides endangered species protection such as recreation use. However, if the habitat has use values, it is also likely that the use values will exhibit distance-decay. In other words, as distance to the habitat increases, we expect that the probability of a “yes” vote will decrease, *ceteris paribus*. We do find a negative estimated coefficient on distance; however, it is not statistically significant in predicting a “vote” on WTP. Two possible reasons exist for this lack of power in prediction for our distance variables. Perhaps the existence value of the Mexican Spotted Owl is such that many people living far away from habitat are willing to pay to protect the owls despite having zero or very small use values for the habitat itself, and thus the lack of significance represents strong existence values, and therefore strong support solely for habitat protection. The ρ parameter remains statistically significant even when the western region variable is included in the specification, indicating

Table 3. Spatial Probit Model Results

Variable	Coefficient	<i>p</i> Value	Total Impacts
Log bid amount	-0.383641	<0.0001	-0.093785
Distance in miles	0.0003	0.2610	0.000073
Distance squared	<0.0001	0.3008	<0.0001
Pro-job	-0.227676	<0.0001	-0.055663
Protect	0.130694	<0.0001	0.031953
Education	0.049784	0.0008	0.012166
Western region	0.306645	0.0824	0.074998
Rho	-0.086	<0.0001	
Mean WTP sample draws			\$59.66
95% CI			[\$15.86–\$253.11]
Mean WTP population draws			\$55.60
95% CI			[\$14.44–\$228.15]

WTP, willingness to pay; CI, confidence interval.

that the ρ parameter is actually measuring dependence within voting behavior.

Another possible reason for the insignificance of distance is a spatial heterogeneity argument—the distance in miles variable does not explicitly take into account spatial groupings of respondents or any sort of feedback effects that may occur through neighborhood differences. The spatial heterogeneity argument is strengthened by the highly significant p value on the spatial autoregressive parameter, ρ . The spatial autoregressive parameter shows the Bayesian equivalence of statistical significance in the spatial probit; thus, we reject the null hypothesis in Equation 8 in favor of the spatial model. The high level of statistical significance associated with ρ indicates that the estimated nonbid coefficients in the standard probit are biased.

With regard to the attitudinal variables, the estimated coefficients on Pro-job and Protect conform to our expectations. Both the standard and spatial models indicate that, *ceteris paribus*, respondents who value job protection are less likely to vote “yes” on the WTP question, whereas respondents who value environmental protection are more likely to vote “yes” on the WTP question. The estimated coefficient on education is positive and significant in both the standard and spatial models, indicating that households with higher educational attainment are more likely to vote “yes” on the WTP question. The

western region indicator variable is statistically significant at the 10% level in the spatial model, although not significant in the standard model. The positive estimated coefficient indicates that respondents living in our western region are more likely to vote “yes” on the WTP question.

Per-household mean WTP is \$54.62 in the standard probit and \$59.66 in the spatial probit. Confidence intervals on WTP are reported in Tables 2 and 3. We also apply the complete combinatorial method to compare the vectors of mean WTP estimates using sample means and obtain a $\hat{\gamma} = 0.86$. 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 hypotheses in Equation 9 and conclude we do not have sufficient statistical evidence to show a significant difference in the empirical distributions of mean WTP from the standard vs. spatial probit. The lack of significant difference may be the result of the large variance in the estimate of WTP from the spatial probit because we have included direct and indirect impacts in our WTP calculation. Nonetheless, with our data, the standard model underestimates WTP per household by \$5.06 per household relative to the spatial model using our sample statistics to calculate WTP.

Differences in Total Population Willingness to Pay Using Spatial and Standard Models

The bias in the nonbid coefficients has economic significance in policy decisions when adjusting the sample WTP to the population WTP. In particular, adjusting for sample unrepresentativeness using attitude or demographic variables requires unbiased estimated demographic coefficients; otherwise, significant errors can occur in the adjusted WTP (Loomis, 1987). In our analysis, we find that is the case. The U.S. Census population estimate of education is 13.1 years vs. the sample estimate of 14.78 years. In our sample, the western region variable is 0.56, whereas in a nationally representative sample, it would be 0.145. A continental U.S. population weighted distance to the Mexican Spotted Owl habitat is approximately 1200 miles rather than the sample average of 560. Replacing just the sample values of these three variables with their U.S. population estimates results in the WTP calculated from the standard model decreasing from the sample average \$54.62 to \$37.65 per household. Performing the same exercise using the spatial model results in a decrease of WTP from \$59.66 to \$55.60. Expanding the approximately \$17 difference times 100 million households could likely result in different conclusions for the amount of Mexican Spotted Owl habitat to protect. In addition, when using the population parameter estimates, the confidence interval on the Krinsky–Robb draws of WTP from the standard probit ranges from –\$10.61 to \$75.71. The credible interval from the Bayesian spatial probit WTP with population parameters ranges from \$14.44 to \$228.15. Therefore, from a practical perspective, although the point estimates are quite similar in the standard and spatial probit models, we find economically significant differences in the models when using them as policymakers would in expanding to the population.

Conclusions

Willingness-to-pay estimates from dichotomous-choice CV surveys are used to inform environmental policies. Many dichotomous-choice CV

surveys estimate values of nonmarket goods in which WTP is likely to depend on distance. In addition, it is likely that unobserved characteristics that impact voting behavior exist within neighborhoods resulting in spatial heterogeneity. If spatial interdependence exists within dichotomous-choice CV data, estimated nonbid coefficients from standard probit models are biased and inconsistent and estimated WTP fails to account for vital spatial spillover effects. Failure to account for vital spatial spillover effects may result in policy-relevant differences in estimated WTP.

In this article, we estimate WTP using a Bayesian spatial probit model and find statistically significant spatial effects to be present. Thus, estimated nonbid coefficients from a standard probit fail to take spatial spillover effects into account and are biased and inconsistent. Although we find different mean 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 statistically different, we do find evidence that the difference in the WTP estimates can result in substantial differences in aggregate or population benefits estimates. In particular, adjusting the sample WTP to the population WTP requires unbiased estimates of the nonbid coefficients. We find the population WTP per household from the standard probit model is \$37.65, which is \$17 less than that of the spatial probit model population WTP of \$55.60.

Given potential differences in estimated WTP, we recommend in nationwide contingent valuation method (CVM) studies that explicit spatial modeling be used. Our data indicate that spatial interdependence can result in biased benefit estimates with potentially important ramifications for policy analyses when using a standard model. We provide an example for researchers on how to proceed with estimation of a Bayesian spatial probit. However, assessing whether spatial interdependence in dichotomous-choice CV is frequently encountered and whether it consistently results in policy relevant differences

in WTP requires more empirical testing using a wide variety of public goods.

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