

The Dual Spatial Autoregressive Probit Model with an Application to the 2001 Congressional Farm Bill

Donald J. Lacombe Garth J. Holloway

Timothy M. Shaughnessy*

March 9, 2009

Abstract

Political economy models of congressional voting usually rely on standard econometric techniques, such as the probit or logit models.

These techniques ignore any spatial externality in voting outcomes that may be geographically correlated across space, a phenomenon

*Donald J. Lacombe is Associate Professor of Economics, Ohio University, Department of Economics, 345 Bentley Annex, Athens, OH, 45701 USA email: lacombe@ohio.edu. Garth J. Holloway is Reader, Department of Agricultural and Food Economics, School of Agriculture, Policy and Development, P. O. Box 237, University of Reading, RG6 6AR, United Kingdom; phone: +(44) +(118) 378-6775; fax: +(44) +(118) 975 6567; e-mail: garth.holloway@reading.ac.uk. Timothy M. Shaughnessy is Associate Professor of Economics, LSU in Shreveport, BE 308, 1 University Place, Shreveport, LA 71115; phone: 1-318-797-5334; email: Timothy.Shaughnessy@lsus.edu

known as spatial autocorrelation. In this paper, we develop and apply the so-called “two W” spatial autoregressive probit model to examine the voting externality in the congressional vote on the 2001 Farm Bill. The “two W” model allows the spatial externality to differ based on two spatial weight matrices, instead of the usual single spatial weight matrix. This configuration of the model allows the testing of spatial voting effects *within* a state versus spatial voting effects *across* state lines. Using recent advances in Bayesian computation, a Gibbs sampling algorithm is developed and implemented to empirically measure the two different spatial autoregressive parameters.

Keywords: spatial probit model, two W spatial model, Bayesian paradigm, Gibbs sampling.

JEL Codes: C11, C21

PRELIMINARY: PLEASE DO NOT QUOTE OR CITE.

1 Introduction

Despite its importance, Congressional voting on agricultural legislation has received little attention in the literature. Noteworthy exceptions (Daft 1964; Fort and Christianson 1981; Brooks, Cameron, and Carter 1988; and Mehmood and Zhang 2001) focus attention on “internalized” determinants of political preferences measured by the impacts of covariates on vote propensities. Yet political lobbying activities, political action committees, and the abilities of

agricultural legislation to be influenced by forces beyond those of individual constituents reflect public, not private actions. In addition, Congressional voting, by its nature, is inherently geographic. The joint existence of “externalized” dependence and geographical inherence draw into question statistical models, such as the standard probit model, that fail to account for political externalities. When such externalities exist it is important to measure their magnitudes, their influence, and the extent of any bias arising in neglecting their presence. Geography is occasionally included in multiple regression models of vote dependence, yet the spatial econometric methods that model spatial dependence have not been fully developed and utilized in empirical studies. In this context two questions arise that warrant further exploration: one is the magnitude of the intensity of the political externality, and the other is the extent of its geographic range.

This article presents procedures for estimating these quantities in the context of investigating the geographic pattern of political preferences in the 2001 Farm Bill. The procedures are based on computational advances in Bayesian inference; provide robust estimates of the intensity and the range of the spatial externality in Congressional voting; and generate nuanced understanding of the complexities underlying agricultural legislation vote outcomes. These procedures have been underutilized in agricultural economics in general and have not been employed previously to measure the spatial externality in agricultural vote outcomes. The spatial probit model (LeSage 2000, Holloway, et. al., 2002) is designed to take into account spatial dependence in the

presence of geographically correlated outcomes. This paper, building on the work of Lacombe (2004), modifies the standard spatial autoregressive probit model (which normally only includes a single weight matrix, W) to include two spatial weight matrices.

2 Motivation and Literature Review

Public choice models of Congressional voting have been studied for decades and a large literature exists on the primary determinants affecting legislators' votes. However, geographic considerations have received less than adequate attention in the econometric specification of such models. Usually, geographic considerations are ignored completely or are handled in an ad hoc manner by specifying regional dummy variables or by using other proxies. For a variety of reasons, the vote of a legislator in one district may be geographically correlated to the vote of a legislator in an adjoining district. As Thorbecke (1997, p. 5) states: “[M]embers of Congress vote to redistribute wealth towards their constituents. It is assumed that they are responsive to both their electoral and geographic constituencies.” Given the assumption that members of congress are responsive to their geographic constituencies, it becomes necessary to outline reasons why there would be differential geographic and spatial effects in congressional voting patterns. For example, it may be the case that a piece of legislation being voted on at the Federal level would help a congressional district in a given state, e.g through some subsidy or

perhaps a spending measure. Hence, it may be expected that there would be spatial dependence in voting outcomes *within* a state. However, the subsidy or spending measure may have effects that spill over into adjoining congressional districts but located in different states. A subsidy to a specific firm may benefit workers in an adjoining state and since Congresspersons are responsive to their constituencies, the Congressperson may also vote for the legislation because even though the legislation isn't directed at their district specifically, the people who live in their district could benefit and hence, may increase the propensity for the Congressperson in the neighboring state to vote for the legislation.

Early interest in agriculture vote outcomes originates from a study of the 1963 Wheat Referendum (Daft, 1964). The referendum was a vote for a government sponsored two-price plan incorporating acreage allotments and land retirement. Daft sought to uncover the determinants of state support for the referendum. Daft's seminal contribution presented empirical findings with substantial content for policy; stemmed interest in the general notion that vote outcomes may "co-vary"; and called forth, somewhat sluggishly, a literature rationalizing vote outcomes in agriculture. Seventeen years after Daft, Fort and Christianson (1981) distinguish strength of preferences for public service provision among rural residents. They analyze referenda votes on hospital provision using logit methodology and conclude, among other findings, that most referenda pass because the economic beneficiaries are geographically concentrated whereas those harmed through higher taxes or debt burden

are more geographically dispersed. Seltzer (1995) examines the creation and passage of the Fair Labor Standards Act (FLSA) of 1938 which establishes a national minimum wage but exempts agriculture. Geographic effects are incorporated by assessing the North-South differences in support for the Act, which imposes the minimum wage only on the relatively lower-wage Southern states. Thorbecke (1997) accounts for geography in assessing the House vote on the North Atlantic Free Trade Agreement (NAFTA) using geographic dummy variables. His results show that geographic and constituent interests strongly influence legislator voting and can sometimes outweigh partisan interests. And a thematic development acknowledging geographic dependence, thus, emerges.

Another thematic development towards political action committee (so-called PAC) contributions was soon to emerge. Wilhite (1988) examines the factors influencing whether a member of Congress votes pro-union, as determined by the American Federation of Labor and Congress of Industrial Organization (AFL-CIO) over the 1984 legislative session. Stratmann's (1992) study on logrolling uses House votes on six amendments to the 1985 farm bill and uses a simultaneous probit model to explain an individual legislator's vote on three different bills individually affecting the dairy, sugar, and peanut industries. Explanatory variables include the percent of farmers in the respective industries in the Congressional district, PAC contributions to the legislator from interests representing the respective industries, and party affiliation and ideological rating as determined by the American Conservative

Union.

Brooks, Cameron, and Carter's (1998) contribution is noteworthy, for several reasons. In addition to promoting further development in the geography-versus-PAC themes, their work also showcases the potential rewards abounding from deeper methodological inquiry. Brooks, Cameron, and Carter (1998) analyze the simultaneous interactions between congressional votes on sugar programs and contributions from both pro- and anti-sugar PACs. The authors employ a simultaneous equations system, with a voting equation and a pro- and anti-sugar contribution equation. The authors use probit and tobit maximum-likelihood for the system for the 1985 and 1990 House votes and the 1990 Senate vote on amendments to omnibus farm bills. Results for the voting equation confirm that greater PAC contributions influence vote probability in the predicted direction, with an unexpected result that anti-sugar contributions are positively associated with a pro-sugar vote in the 1990 House vote. Results for the contributions equations confirm that a greater propensity to vote pro-sugar leads to greater pro-sugar PAC contributions and less to anti-sugar PAC contributions, except in the case of the 1985 House vote where the anti-sugar contribution coefficient is significantly positive.

Following Brooks, Cameron, and Carter (1998) contributions appear which, although stridently relevant to the topic at hand, impact agriculture somewhat less directly. Mehmood and Zhang (2001) identify the factors affecting legislator votes in four selected House Endangered Species Act amendments

proposed since passage. Hasnat and Callahan (2002) examine the determinants of Congressional votes on the 2000 bill to normalize trade relations with China. Colburn and Hudgins (2003) examine votes on legislation affecting the banking industry’s interstate branching and find relatively strong geographic influences. Collectively these contributions indicate the diversity of interest in the political economy of agricultural legislation formation, the over-arching importance of PAC contributions in agriculture and the inherently geographic nature of the industry and the legislators who vote to affect it. However, they serve also to illustrate a neglect of possibilities for a spatial externality in voting and they therefore raise scope for nuanced empirical inquiry.

3 Spatial Econometric Models

The model that we employ is a variant of a standard spatial econometric model, namely the spatial autoregressive model (SAR). LeSage (1997) provides a tutorial on the basics of using Bayesian methods to estimate the model, which captures spatial dependence in the dependent variable for continuous outcomes. Our probit extension begins with the so-called “two W” SAR model as utilized by Lacombe (2004) for continuous outcomes

$$y = \rho_1 W_1 y + \rho_2 W_2 y + X\beta + \varepsilon$$

$$\varepsilon \sim N(0, \sigma^2 I_n)$$

where y is a $n \times 1$ vector of observations, ρ_1 is the spatial dependence parameter for the first weight matrix, ρ_2 is a similar parameter for the second weight matrix, X is the design matrix, ε is the error term, and W_1 and W_2 are unique weight matrices designed to capture spatial dependence within a state (using W_1) versus spatial dependence across state lines (using W_2). Solving for y in the above equation gives us the following data generating process (DGP)

$$\begin{aligned} y - \rho_1 W_1 y - \rho_2 W_2 y &= X\beta + \varepsilon \\ (I_n - \rho_1 W_1 - \rho_2 W_2) y &= X\beta + \varepsilon \\ y &= (I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} X\beta + (I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} \varepsilon \end{aligned}$$

We now turn our attention to the Bayesian estimation of the two W spatial probit model, which is an extension of the basic spatial autoregressive probit model developed by LeSage (2000). For further extensions to the basic spatial probit model, including the spatial Tobit and spatial Multinomial Probit models, please see LeSage and Pace (2009), and for a tutorial on Bayesian estimation in spatial regression models, please see Lacombe (2008).

4 Statistical Model

Beginning with some general notation that will serve throughout this paper, let θ denote a collection of parameters of interest, $\pi(\theta)$ the prior probability density function (pdf) for θ , and $\pi(\theta|y)$ the posterior pdf for θ , where $y \equiv (y_1, y_2, \dots, y_N)'$ denotes data. The data generating model $f(y|\theta)$, which is the likelihood function when viewed as a function of θ , appears in various forms representing particular probability density functions. There are two pdfs that we employ, namely the multivariate-normal pdf, $f^{MVN}(\cdot|\cdot)$, and the truncated-normal pdf $f^{TN}(\cdot|\cdot)$. Often, we reference just the variable part of the density by noting its proportionality (integrating constant excluded) with reference to a true pdf (integrating constant included) by using the symbol “ \propto ”.

An estimable model of Congressional voting evolves in three steps. First, we specify the legislator’s relationship between their propensity to vote in favor of the 2001 Farm Bill and their observed characteristics; second, we permit neighboring decisions (i.e. neighbors within a state and neighbors across state lines) to impact the congressperson’s own decisions; third, we formulate a statistical model of the congressperson based on their discrete choice and, subsequently, devise an estimation strategy for drawing inferences from the probability model. In deriving marginal distributions complications force us to draw inferences using iterative procedures referred to, generically, as Markov Chain Monte Carlo methods (MCMC). Application of MCMC

follows seminal work by Gelfand and Smith (1990). Useful introductions to MCMC and their use in Bayesian inference are Casella and George (1992), Chib and Greenberg (1995) and Robert and Casella (1999).

The structural model for our two W spatial autoregressive probit model takes the following form

$$\begin{aligned} y^* &= \rho_1 W_1 y^* + \rho_2 W_2 y^* + X\beta + \varepsilon \\ \varepsilon &\sim MVN(0, \sigma^2 I_n) \end{aligned}$$

which can be written in reduced form as the following

$$\begin{aligned} y^* &= (I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} X\beta + u \\ u &= (I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} \varepsilon \end{aligned}$$

The latent variable y^* links to the observed binary outcome, y through the measurement equation

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases}$$

As shown above, the error term ε is distributed multivariate normal with

mean 0 and variance-covariance matrix $\sigma^2 I_n$. We set $\sigma^2 = 1$, which is the standard assumption required for identification in the probit model (see, for example, Greene, 2008, p. 776). The distribution of u is derived in the following manner¹

$$\begin{aligned} V \left[(I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} \varepsilon \right] &= \left[(I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} \right]' V(\varepsilon) \left[(I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} \right] \\ &= \left[(I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} \right]' \sigma^2 I_n \left[(I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} \right] \\ &= \left[(I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} \right]' \left[(I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} \right] \end{aligned}$$

From this it can be seen that u is distributed multivariate normal with mean 0 and variance-covariance matrix $\left[(I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} \right]' \left[(I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} \right]$.

The two separate W matrices deserve special attention. The first spatial weight matrix, W_1 denotes the three nearest neighbors *within* a state, i.e. congressional districts that are wholly contained within the borders of a single state. The second spatial weight matrix, W_2 are the three nearest neighbor congressional districts that are adjacent to each other *but in different states*. The use of these two separate weight matrices will allow for the examination of the spatial relationship between congressional votes and the specific pattern of spillovers over geographic space. Thus, we are able to empirically measure two different types of spillover effects in congressional

¹The u term is of interest because like the standard probit, we are interested in how the systematic component $\left[(I_n - \rho_1 W_1 - \rho_2 W_2)^{-1} X\beta \right]_i / \sigma_i$ exceeds the stochastic component, u_i .

voting patterns.

Continuing with the development of the statistical model, we observe data X , assign data for the two separate weight matrices W_1 and W_2 , and observe $y \equiv (y_1, y_2, \dots, y_N)'$, where $y_i = 1$ if congressperson i votes for the legislation and $y_i = 0$ otherwise. We do not observe $\theta \equiv (\beta', \rho_1, \rho_2)'$ and our objective is to characterize the locations and scales of the marginal distributions $\pi(\rho_1 | y)$, $\pi(\rho_2 | y)$, and $\pi(\beta | y)$. In deriving these distributions we need to establish the form of the joint posterior density $\pi(\theta | y)$, which is proportional to the likelihood for the data, $f(y | \theta)$, and the prior pdf $\pi(\theta)$. The reader will note that one important feature of the problem is the absence of the latent data, z , which, by definition, are not observed. Therefore, one key step in the estimation involves augmenting the *observed data likelihood*, $f(y | \theta)$, with these latent quantities yielding the *complete data likelihood*, $f(y | \theta, z)$, and the associated *posterior pdf*, $\pi(\theta | y, z)$, defined with respect to both the observed and the missing data. The advantages of augmenting models with latent data are highlighted in a series of influential papers by Siddhartha Chib and co-authors (Chib, 1992; Albert and Chib, 1993; and Chib, 1996).

Due to complexities arising from the joint features of the binary nature of the data and the probit-link underlying the likelihood function, the integrations required to obtain the marginal probability density functions $\pi(\rho_1 | y)$, $\pi(\rho_2 | y)$ and $\pi(\beta | y)$ are not available in closed form. However, we are able to easily derive the set of fully conditional distributions required for Gibbs sampling, namely $\pi(\rho_1 | \rho_2, \beta, y, z)$, $\pi(\rho_2 | \rho_1, \beta, y, z)$, and $\pi(\beta | \rho_1, \rho_2, y, z)$.

The full conditional distributions for the two spatial autoregressive parameters, $\pi(\rho_1 | \rho_2, \beta, y, z)$, and $\pi(\rho_2 | \rho_1, \beta, y, z)$ do not correspond to any known probability distribution. In these scenarios, it is relatively straight-forward to simulate draws using a random-walk Metropolis-Hastings algorithm (see Robert and Casella, 1999, pp. 245-246, for details). These features of the statistical model lead naturally to a robust algorithm for estimating the two W spatial autoregressive probit model consisting of Gibbs sampling the fully conditional distributions of the complete data model, $\pi(\theta | y, z)$, simulating directly from $\pi(\beta | \rho_1, \rho_2, y, z)$, and simulating directly from $\pi(\rho_1 | \rho_2, \beta, y, z)$ and $\pi(\rho_2 | \rho_1, \beta, y, z)$ using a random-walk Metropolis step. Sampling in turn from each of the corresponding full conditional distributions and collecting the output for a pre-specified number of iterations allows for inference regarding the location and scale of each posterior distribution and whether or not spatial dependence exists in the 2001 Congressional Farm Bill vote.

5 Derivation of the Full Conditional Distributions

In order to derive the full conditional distributions, we need to first assess the form of the joint posterior, $\pi(\theta | y, z)$, which is proportional to the product of the complete data density, $f(y | \theta, z)$, and the prior pdf, $\pi(\theta)$. We assume prior independence between ρ_1 , ρ_2 , and β , assume a univariate normal pdf for both ρ_1 and ρ_2 , namely $\pi(\rho_1 | \rho_{1_0}, \sigma_{1_0})$ and $\pi(\rho_2 | \rho_{2_0}, \sigma_{2_0})$, and assume a

multivariate-normal pdf for β , namely $\pi(\beta | \beta_0, C_0^{-1})$.

As mentioned earlier the standard probit likelihood function, which is defined as the following $\prod_{i=1}^N [\Phi(x'_i\beta)]^{y_i} [1 - \Phi(x'_i\beta)]^{1-y_i}$, is complicated by the presence of the integrals implicit in the cumulative normal distribution functions $\Phi(x'_i\beta)$, $i = 1, 2, \dots, N^2$. However, Albert and Chib (1993) show that intractabilities can be easily circumvented by augmenting the observed data likelihood $f(y|\theta)$ with the latent responses, z , and, instead, focusing attention on the complete data likelihood $f(y|\theta, z) \equiv f^N(z|X\beta, I_N)$. LeSage and Pace (2009, p.282) note that "... we can use the same conditional posterior distributions that arise for the case of a continuous dependent variable regression model." In other words, the spatial probit model is converted into a continuous dependent variable model because we are able to sample for the latent quantities. Thus, derivation of the full conditional distributions follows conventional methods.

Defining $A \equiv (I_n - \rho_1 W_1 - \rho_2 W_2)$, the form of the joint posterior distribution is given by the following

$$\pi(\theta|y) \propto |A| \exp\{-.5(Az - X\beta)'(Az - X\beta)\} \pi(\beta) \pi(\rho_1) \pi(\rho_2)$$

where $\pi(\beta)$ represents the prior on the β 's, $\pi(\rho_1)$ represents the prior on the ρ_1 parameter, and $\pi(\rho_2)$ represents the prior on the ρ_2 parameter.

²Franzese and Hays (2008, p. 7-8) note that "Because each unit's outcome is interdependent, their joint distribution is not the product of the n marginal distributions, so one does not maximize sums of logs of n one-dimensional probabilities, but interdependent and so one maximizes the log of one n -dimensional distribution."

The full conditional distributions are derived from the joint posterior distribution and take the following form

$$\begin{aligned} \pi(\beta | \rho_1, \rho_2, y, z) &\propto \exp\{-.5(Az - X\beta)'(Az - X\beta)\} \\ &\times \exp\{-.5(\beta - \beta_0)'C_0^{-1}(\beta - \beta_0)\} \end{aligned} \quad (1)$$

$$\pi(z | \rho_1, \rho_2, \beta, y) \propto \exp\{-.5(Az - X\beta)'(Az - X\beta)\} \quad (2)$$

$$\begin{aligned} \pi(\rho_1 | \rho_2, \beta, y, z) &\propto |A| \exp\{-.5(Az - X\beta)'(Az - X\beta)\} \\ &\times \exp\{-.5\sigma_{1_0}^{-2}(\rho_1 - \rho_{1_0})^2\} \end{aligned} \quad (3)$$

$$\begin{aligned} \pi(\rho_2 | \rho_1, \beta, y, z) &\propto |A| \exp\{-.5(Az - X\beta)'(Az - X\beta)\} \\ &\times \exp\{-.5\sigma_{2_0}^{-2}(\rho_2 - \rho_{2_0})^2\} \end{aligned} \quad (4)$$

The distribution in (1) is proportional to the multivariate-Normal distribution with mean $(X'X + C_0^{-1})^{-1}(X'Az + C_0^{-1}\beta_0)$ and covariance $(X'X + C_0^{-1})^{-1}$. Therefore, β is distributed f^{MVN} with mean $(X'X + C_0^{-1})^{-1}(X'Az + C_0^{-1}\beta_0)$ and covariance $(X'X + C_0^{-1})^{-1}$.

The distribution in equation (2) is proportional to the multivariate-Normal distribution with mean $\delta \equiv (A'A)^{-1}A'X\beta$ and covariance $\Sigma \equiv (A'A)^{-1}$ subject to each component of z satisfying sign restrictions embodied in y . Specifically, for $i = 1, 2, \dots, N$, $z_i > 0$ if $y_i = 1$ and $z_i \leq 0$ if $y_i = 0$. In order to obtain efficient one-for-one draws for each element of z , we apply the ‘‘probability integral transform’’ (see, for example, Mood et al., 1974, pp.

202-203) to the N fully conditional distributions defined with respect to the joint distribution for z , $f^{TN\pm y}(z|\delta, \Sigma)$, where the notation “ $\pm y$ ” signifies the dependence of the signs of each component of z on the corresponding component in y . The explicit conditional distributions are derived by exploiting standard results on the relationship between the joint and conditional distributions of the multivariate-Normal pdf (see, for example, Zellner, 1996, pp. 378-93), for which some additional notation proves helpful. Define μ_i as the i^{th} component of the N -vector $\mu \equiv X\beta \equiv (\mu_1, \mu_2, \dots, \mu_N)'$; define μ_{-i} as the $(N-1)$ vector retained once the i^{th} element is removed; define Σ_{ii} as the i^{th} row, i^{th} column element of Σ ; define Σ_{-i-i} as the $(N-1) \times (N-1)$ matrix remaining after the i^{th} row and i^{th} column are removed; define Σ_{i-i} as the $(N-1)$ row vector obtained by removing the i^{th} column from the i^{th} row of Σ ; and define Σ_{-ii} as the $(N-1)$ column vector obtained by removing the i^{th} row from the i^{th} column of Σ . With this notation we can establish that each z_i , $i = 1, 2, \dots, N$, has the truncated-normal distribution $f^{TN\pm y_i}(z_i|\delta_i, \sigma_i)$, $\delta_i \equiv \mu_i + \Sigma_{i-i}\Sigma_{-i-i}^{-1}(z_{-i} - \mu_{-i})$ and $\sigma_i \equiv \Sigma_{ii} - \Sigma_{i-i}\Sigma_{-i-i}^{-1}\Sigma_{-ii}$.

A draw from equations (3) and (4) is simulated using a random-walk, Metropolis-Hastings step. We begin by generating proposal values, τ_1 and τ_2 , from $f^N(\tau_1|\rho_1, \xi_1)$ and $f^N(\tau_2|\rho_2, \xi_2)$, where ρ_1 and ρ_2 denote the current value of the spatial dependence parameter and ξ_1 and ξ_2 denote the standard deviation of the Normal distributions generating the proposal values. Define the following

$$\begin{aligned}
\Pi &\equiv I_n - \tau_1 W_1 - \tau_2 W_2 \\
f(\tau_1, \tau_2 | \beta, y, z) &= |\Pi| \exp \left\{ -0.5 (\Pi z - X\beta)' (\Pi z - X\beta) \right\} \\
&\quad \times \exp \left\{ -0.5 \sigma_{10}^{-2} (\tau_1 - \rho_{10})^2 \right\} \exp \left\{ -0.5 \sigma_{20}^{-2} (\tau_2 - \rho_{20})^2 \right\} \\
f(\rho_1, \rho_2 | \beta, y, z) &= |A| \exp \left\{ -0.5 (Az - X\beta)' (Az - X\beta) \right\} \\
&\quad \times \exp \left\{ -0.5 \sigma_{10}^{-2} (\rho_1 - \rho_{10})^2 \right\} \exp \left\{ -0.5 \sigma_{20}^{-2} (\rho_2 - \rho_{20})^2 \right\}
\end{aligned}$$

The proposal draw for the spatial dependence parameters are accepted with the probability $\varphi \equiv \min \{f(\tau_1, \tau_2 | \beta, y, z) / f(\rho_1, \rho_2 | \beta, y, z), 1\}$. Thus, the sampling routine for estimating the parameters of the two W spatial autoregressive probit model is defined by the following algorithm

1. Simulate a draw for β from $f^{MVN} \left((X'X + C_0^{-1})^{-1} (X'Az + C_0^{-1}\beta_0), (X'X + C_0^{-1})^{-1} \right)$
2. Simulate draws for z $i = 1, 2, \dots, N$ from $f^{TN \pm y_i} (z_i | \delta_i, \sigma_i)$
3. Simulate a draw from $f^N(\tau_1 | \rho_1, \xi_1)$ and $f^N(\tau_2 | \rho_2, \xi_2)$ and accept the draw with probability $\varphi \equiv \min \{f(\tau_1, \tau_2 | \beta, y, z) / f(\rho_1, \rho_2 | \beta, y, z), 1\}$

6 Data and Results

The legislation under consideration is the conference report HR 2646 arising in the second session of the 107th Congress (which met in 2001 through 2002). In the House, the bill was known as the *Farm Security Act of 2001*.

Data on the House vote (Roll Call 123, taken May 2, 2002) are collected at the Clerk of the House website³, and an individual observation in our dataset corresponds to each Representative who was available to vote on HR 2646. The binary variable “YEA” is recorded as a “1” for a vote in favor of the conference report and recorded as a “0” for a vote against the report or if the Representative did not vote. The binary variable DEMOCRAT is coded as “1” for Democrats and “0” for Republicans or Independents, and is collected from the House Office of the Clerk’s Official List of Members website⁴. Congressional district information for the Representatives is also collected at the House Clerk Official List website. There are 348 votes, of which 233 are “yeas” and 115 are “nays.”

To measure political influence, we include a dummy variable AGCOM which equals ‘1’ if the Representative sat on the House Committee on Agriculture in the 107th Congress. Support for agricultural legislation could arguably be influenced by a legislator’s ideology, so we include a dummy variable DEMOCRAT which equals “1” if the legislator was a member of the Democratic Party and “0” otherwise. A last measure that we include in order to assess the influence of agriculture in the district is the amount of urbanization. Assuming an inverse relationship between the degree of urbanization and the strength of support for agriculture legislation, we use the variable URBAN, which is the proportion of urban dwellers obtained from

³<http://clerk.house.gov/evs/2002/roll123.xml>

⁴http://clerk.house.gov/histHigh/Congressional_History/olm.html?congress=107h

the Census 2000 Summary File 1 for each Congressional District.

In order to measure the influence of agriculture political interests on individual members of Congress, we use data from the Center for Responsive Politics' Opensecrets.org website, which compiles campaign contribution information in U.S. elections. For our purposes, we use reports on the Members of the 107th Congress⁵. For each member, we create the variable AGPAC by dividing the total amount of PAC money received by the member by the amount of money contributed by "agribusiness" PACs over the 2001-2002 period. We note that four of the observations on PAC contributions are negative. Data on contributions are collected on a two-year cycle consistent with the election cycle; a negative PAC contribution for the 2001-2002 period indicates that a contribution had been made to the candidate prior to 2001 but had been returned to the donor during the 2001-2002 cycle. Similarly, a PAC may have made a donation to the candidate during the 2001-2002 cycle and if the full amount was returned later in the same cycle, the PAC contributions variable would have the value zero. Finally, values of production and government payments are incorporated. Both measures are obtained from the National Agricultural Statistics Service's (NASS) 2002 Census of Agriculture⁶. The variable MVP (market value of production) is the average market value of production per farm in dollars and is intended to measure the relative size and perhaps influence of farms in a Congressional district.

⁵<http://www.opensecrets.org/politicians/candlist.asp?Sort=S&Cong=107>

⁶http://www.nass.usda.gov/Census_of_Agriculture/

The GP (government payments) variable is the average government payment per farm in dollars for those farms that receive payments. This variable is included in order to determine if farms receiving payments exert influence. Given that NASS does not disclose some of the data on government payments due to privacy concerns, the sample size is effectively reduced to 348 observations.

The econometric model that we estimate is as follows

$$y = \rho_1 W_1 y + \rho_2 W_2 y + X\beta + \varepsilon$$

where y is an $n \times 1$ vector of observations on the dependent variable, X is the $n \times k$ matrix of independent variables, ρ_1 and ρ_2 are spatial dependence parameters, and W_1 and W_2 are $n \times n$ spatial weight matrices. W_1 is a weight matrix that is formed by finding the three nearest congressional district neighbors *within* a state, and W_2 is a weight matrix that is formed by finding the three nearest congressional district neighbors *across* a state's border. The first weight matrix is designed to capture spatial dependence in votes within a state and the second weight matrix is designed to capture spatial dependence that may exist across state borders. Each of the weight matrices are standardized via the spectral density method of Kelejian and Prucha (2007), whereby each element of the weight matrix is divided by its

largest eigenvalue in absolute value⁷.

In our Gibbs sampling routine, we utilize 10,000 draws for the burn-in period, followed by 10,000 draws for the actual sampling. We also utilize proper priors, albeit with diffuse values⁸.

Table 1 contains our results from the Gibbs sampling exercise. The first column in Table 1 lists the explanatory variables used in the analysis, the second column contains the point estimates for each variable⁹, and the final column lists the 95% credible intervals for each coefficient estimate.¹⁰

The results are noteworthy and confirm our hypotheses regarding the spatial dependence parameters as well as our hypotheses regarding the independent variables. First, it appears that there is positive spatial dependence in the voting patterns on the 2001 Farm Bill in congressional districts within a state, as evidenced by the ρ_1 parameter of 0.22, albeit a relatively small dependence. Additionally, the second spatial dependence parameter ρ_2 also shows that there is positive spatial dependence in congressional districts that are adjacent but in different states, with again a relatively small value of 0.09.

⁷Kelejian and Prucha (2007, p. 7-9) note that using the spectral density row normalization bounds the ρ parameters between $(-1, 1)$ and also state "... unless theoretical issues suggest a row-normalized weights matrix, this approach in general will lead to a misspecified model."

⁸Specifically, we use a vector of zeros for our prior on the coefficients, zeroes for the priors on the spatial dependence parameters, a covariance matrix of $(100 \times I_n)$ for the β 's, and a value of 100 for the variance on each ρ parameter.

⁹The point estimates are defined as the the mean of the posterior distribution for each β . It should be noted that these coefficient estimates are *not* the associated marginal effects.

¹⁰Koop (2003), pp. 43-45, contains information on the building and interpretation of credible intervals.

This result appears to validate the idea that Congressional dependence is the 2001 Farm Bill vote can be broken down into two separate spatial components, with a greater strength of dependence within states as opposed to across state lines.

In terms of the set of independent variables used in the analysis, standard results that have appeared in the previous literature seem to apply in this case as well. The positive coefficient estimate on the DEMOCRAT variable indicates that House members who belong to the Democratic Party are more likely to vote for the 2001 Farm Bill. The Democratic Party has long been associated with the interests of farmers and this results is a fairly standard one that is found in the literature. The URBAN variable is one that has the expected sign and association with the voting patterns of representatives. People living in urban areas may not think that they have any real interest in farming issues, and in fact may view farm programs as a wealth transfer from urban dwellers to their rural counterparts¹¹. We would expect that representatives from urban areas would be less inclined to vote for any farm-related legislation and our empirical results seem to confirm this hypothesis. Another ubiquitous covariate found in the literature is a measure of financial support from industry. The PAC variable we use is designed to capture any influence of political action committee contributions on legislative outcomes and it is no surprise that this variable has a positive impact on voting pat-

¹¹There is anecdotal evidence that Congresspersons from urban areas form alliances with other groups (e.g. environmentalists) in opposing farm programs.

terns on the 2001 Farm Bill. Finally, our MVP variable (market value of production) has a negative coefficient estimate, indicating that as the market value of production decreases, the propensity to vote for the Farm Bill decreases as well. However, the magnitude of the coefficient estimate is so small that it seems that this variable has very little substance from an economic significance perspective. Finally, we note that the variables AGCOM (a dummy representing those who sit on the Agricultural Committee) and GP (government payments) seem to have no influence on the voting habits of members of Congress.

7 Conclusion

The estimation of spatial econometric models, such as the spatial probit, has been greatly facilitated by Bayesian methods as outlined in a series of influential articles by LeSage (1997, 2000) and LeSage and Pace (2009, Chapter 10). Building on these pioneering efforts, we develop and utilize the Dual Spatial Autoregressive probit model and empirically investigate whether or not there is differential spatial impacts in Congressional voting on the 2001 Farm Bill. Our results indicate that indeed there are differential impacts and that the spatial impacts are stronger in congressional districts within a state as opposed to the effect across state borders. We also find that covariates associated with being a member of the Democratic Party, living in an urban area, and political action committee contributions have a positive impact on

the propensity of a congressperson to vote in favor of the 2001 Farm Bill.

Future research will include the development of the two W spatial error probit model, which is designed to model unobserved factors that vary systematically over geographic space in the context of a discrete choice model, the calculation of marginal likelihoods to enable appropriate model comparisons, and the empirical question of what configuration of the W matrix is appropriate.

8 References

Albert, J. H., and S. Chib. 1993. "Bayesian Analysis of Binary and Polychotomous Response Data." *Journal of the American Statistical Association* 88(422):669-79.

Brooks, J. C., A. C. Cameron, and C. A. Carter. 1998. "Political Action Committee Legislation and U.S. Congressional Voting on Sugar Legislation." *American Journal of Agricultural Economics* 80(3):441-454.

Casella, G., and E. I. George. 1992. "Explaining the Gibbs Sampler." *American Statistician* 46(3):167-74.

Chib, S. 1992. "Bayes Inference in the Tobit Censored Regression Model." *Journal of Econometrics* 51(1-2):79-99.

Chib, S., and E. Greenberg. 1995. "Understanding the Metropolis-Hastings Algorithm." *American Statistician* 49(4):327-35.

Chib, S. 1996. "Calculating posterior distributions and modal estimates in Markov mixture models." *Journal of Econometrics* 75(1):79-97.

Colburn, C. B., and S. C. Hudgins. 2003. "The Intersection of Business, State Government, and Special Interests in Federal Legislation: An Examination of Congressional Votes on the Road to Interstate Branching." *Economic Inquiry* 41(4):620-638.

Daft, L. M. 1964. "The 1963 Wheat Referendum: An Interpretation." *Journal of Farm Economics* 46(3):588-592.

Fort, R., and J. B. Christianson. 1981. "Determinants of Public Services Provision in Rural Communities: Evidence from Voting on Hospital Referenda." *American Journal of Agricultural Economics* 64(2):228-236.

Franzese, R. J. and J. C. Hays. 2008. "The Spatial Probit Model of Interdependent Binary Outcomes: Estimation, Interpretation, and Presentation" (March 31, 2008). Available at SSRN: <http://ssrn.com/abstract=1116393>

Gelfand A E, and A. F. M. Smith. 1990. "Sampling-Based Approaches to Calculating Marginal Densities." *Journal of the American Statistical Association* 85(410):398-409.

Greene, W.H. 2008. *Econometric Analysis*. Upper Saddle, NJ: Prentice-Hall.

Hasnat, B., and C. Callahan III. 2002. "A Political Economic Analysis of Congressional Voting on Permanent Normal Trade Relations of China." *Applied Economics Letters* 9(7):465-468.

Holloway, G., B. Shankar, and S. Rahman. 2002. "Bayesian Spatial Probit Estimation: A Primer and an Application to HYV Rice Adoption." *Agricultural Economics* 27(3):383-402.

Kelejian, H. J. and I. Prucha. "Specification and Estimation of Spatial Autoregressive Models with Autoregressive and Heteroskedastic Disturbances" Forthcoming in the *Journal of Econometrics*.

Koop, G. 2003. *Bayesian Econometrics*. Chichester: Wiley.

Mehmood, S. R., and D. Zhang. 2001. "A Roll Call Analysis of the Endangered Species Act Amendments." *American Journal of Agricultural Economics* 83(3):501-512.

Lacombe, D. J. 2004. "Does Econometric Methodology Matter? An analysis of Public Policy Using Spatial Econometric Techniques" *Geographical Analysis* 36(2):105-118.

Lacombe, D. J. 2008. "An Introduction to Bayesian Inference in Spatial Econometrics" Available at SSRN: <http://ssrn.com/abstract=1244261>

LeSage, J. P. 1997. "Bayesian Estimation of Spatial Autoregressive Models." *International Regional Science Review* 20(1-2):113-29.

LeSage, J.P. 2000. "Bayesian Estimation of Limited Dependent Variable Spatial Autoregressive Models." *Geographical Analysis* 32(1):19-35.

LeSage, J. P. and R. K. Pace. 2009. *Introduction to Spatial Econometrics*. Boca Raton: CRC Press.

Mood, A. M., F. A. Graybill, and D. Boes. 1974. *Introduction to the Theory of Statistics* (McGraw-Hill Series in Probability and Statistics). 3d ed. New York: McGraw-Hill.

Robert, C. P., and G. Casella. 1999. *Monte Carlo Statistical Methods*. New York: Springer-Verlag.

Seltzer, A. J. 1995. "The Political Economy of the Fair Labor Standards Act of 1938." *The Journal of Political Economy* 103(6):1302-1342.

Stratmann, T. 1992. "The Effects of Logrolling on Congressional Voting." *The American Economic Review* 82(5):1162-1176.

Thorbecke, W. 1997. "Explaining House Voting on the North American Free Trade Agreement." *Public Choice* 92(3-4):231-242.

Wilhite, A. 1988. "Union PAC Contributions and Legislative Voting."
Journal of Labor Research 9(1):79-90.

Zellner, A. 1996. *An Introduction to Bayesian Inference in Econometrics* (Wiley Classics Library). New York: John Wiley and Sons.

Table 1: Dual Spatial Autoregressive Model Estimates
 Dependent Variable: “Yea” or “Nay” on Farm Bill Vote

Explanatory Variables	Estimated Coefficient	95% Credible Interval
Constant	1.70	[1.09, 2.33]*
Democrat	0.41	[0.14, 0.68]*
Ag Committee	0.48	[-0.08, 1.08]
Urban	-2.16	[-2.92, -1.41]*
Ag Pac Money	3.76	[1.55, 6.01]*
Market Value	-0.00000079	[-0.0000015, -0.000000021]*
Govt Payments	0.0000071	[-0.0000070, 0.000022]
ρ_1	0.22	[0.07, 0.37]*
ρ_2	0.09	[0.006, 0.22]*
Number of Observations=348		

Note: Entries in the 95% Confidence Interval field marked with an asterisk indicate intervals that do not contain zero.