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How Large Is Congressional Dependence in Agriculture? Bayesian Inference About 'Scale' And 'Scope' In Measuring A Spatial Externality

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Abstract

The political economy literature on agriculture emphasizes influence over political outcomes via lobbying conduits in general, political action committee contributions in particular and the pervasive view that political preferences with respect to agricultural issues are inherently geographic. In this context, 'interdependence' in Congressional vote behaviour manifests itself in two dimensions. One dimension is the intensity by which neighboring vote propensities influence one another and the second is the geographic extent of voter influence. We estimate these facets of dependence using data on a Congressional vote on the 2001 Farm Bill using routine Markov chain Monte Carlo procedures and Bayesian model averaging, in particular. In so doing, we develop a novel procedure to examine both the reliability and the consequences of different model representations for measuring both the 'scale' and the 'scope' of spatial (geographic) co-relations in voting behaviour.

***Keywords**:* Congressional vote dependence, Bayesian spatial probit, Markov chain Monte Carlo methods, Bayesian model averaging, political economy, spatial correlations, PAC contributions and their effectiveness

***JEL Classifications**:* H11, C31, C11.

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Bayesian Inference About 'Scale' And 'Scope'
In Measuring A Spatial Externality

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 'constituent-internalized' determinants of political preferences measured by the impacts of covariates on voting propensities of constituents. Yet, political lobbying activities, political action committees, and other collective, rather than private, actions also influence agricultural legislation. In addition, Congressional voting, by its nature, is inherently geographic. The joint existence of 'collective-externalized' dependence and geographical influence raise questions about statistical models 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 of political economy. Two, important questions arising warrant further exploration: the intensity of the political externality; the extent of its geographic range.

We present procedures for answering these questions through an investigation of the geographic pattern of political influence in the 2001 Farm Bill. Our procedures are based on computational advances in Bayesian inference. They provide robust estimates of both the intensity of geographical interdependence and the range of the spatial externality in Congressional voting. In so doing, they generate a more nuanced understanding of the complexities underlying US farm legislation vote outcomes. Section two presents a brief review of the relevant literature; section three outlines our estimation procedures; and section four presents the data used in the empirical application. The results are presented in section five and section six concludes.

2. Motivation

Public choice models of Congressional voting have been studied for decades and a large literature exists on the primary determinants affecting legislators' votes. However, less is so in agriculture. Thematic developments in the general literature related to 'the political economy of agricultural policy,' are available in the comprehensive review within the *Handbook of Agricultural Economics* series, contributed by de Gorter and Swinnen (2002). Their review of the extant literature (up until 2002), identifies several important, independent themes emerging in the political-economy-within-agriculture setting. Considerable attention is devoted toward general agricultural policy interventions (see, for some fairly heterogeneous, general examples, Schultz, 1978; Gardner, 1987; Alston and Carter, 1990; de Gorter and Tsur, 1991; and Binswanger and Deininger, 1997). Specific attention is devoted to: (a) protections across countries, sectors and over time (see, for example, Fulginiti and Shogren, 1992; Beghin and Kerallah, 1994); (b) the influence of political institutions (for example, Rausser, 1982); (c) developing a framework for analysis of multifaceted political factors, including *collective action by lobby groups* (as motivated by Olson, 1971, 1985), *political support function initiatives* (Peltzman, 1976; Hillman, 1982; Swinnen and de Gorter, 1993; Swinnen, 1994), *strategic interaction between lobby groups and politicians* (for example, Zwart and Meilke, 1979; Beghin, 1990; Bullock, 1994; and Bullock, 1995), *empirical studies of revealed preference* (Rausser and Freebairn, 1994), and *empirical studies of lobbying and politician behaviour* (see, for a comprehensive set of examples, de Gorter, 1983). Coverage of important, although, perhaps, ancillary, questions, at least to present purposes; such as explaining the use of inefficient instruments (see, for example, Swinnen et al., 2000), empirically assessing the importance of inefficient instruments (Swinnen et al., 2012) and explaining public investments in agricultural research (see the literature cited in Anderson et al., 1994) lead to a well-rounded coverage, with few, remaining agenda's for future research. Notwithstanding this conclusion, one notably absent feature of this comprehensive coverage is the issue of spatial interconnection or the extent to which spatial inter-dependence could impact political actions. Thus, scope exists for detailed examination.

Geographic considerations have received very little 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. However, 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. This may be due merely to the fact that adjoining regions share similarities, to a desire for homogeneity between trading regions, or to serendipity. 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." Yet, by and large, discrete-choice, political-economy contributions – including those in agriculture – have failed to take full account of the importance of geographic constituency.

A typical tool in these studies is the probit model, which generates the so-called 'marginal effects' measuring the likelihood that a change in a covariate affects a vote outcome, which have significant implications for policy. In voting parlance, relevant to political action committee

(PAC) contributions, these marginal effects are the additional contributions required to achieve either a 'yea' or a 'nay' vote. Given the apparent significance of these contributions, it is not surprising that they have become extremely sensitive and, at times, emotionally laden instruments in the formation of government policy. This important feature of the political economy of agriculture begs three questions. First, are the marginal probabilities derived from standard political economy investigations affected by externalities in voting behaviour? Second, if so, then, by how much? Third, can we estimate the precise *magnitude* and geographic *scope* of these voting externalities? We note here that the geographic externality has both 'scope' and 'scale' components, which we explore in our empirical approach

We exploit a Bayesian spatial probit model and link it to recent developments in the literature on Bayesian model selection and Bayesian model averaging. While this analysis demonstrates the methodology, it also contributes to understanding a long-established interest in vote behaviour.

Early interest 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. Over a million wheat farmers in the US voted. The referendum was defeated, garnering only 48 percent support when it needed a two-thirds majority for passage. Daft sought to uncover the determinants of state support for the referendum. She used as the dependent variable the percentage voting 'yes' in each of 28 states (the 28 that had at least 5000 farmers voting). The biggest factor contributing to a 'yes' vote (negatively, it emerges) is the percentage of farmers in the state who were considered to be 'part-time.' 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. Fifteen years after Daft, Fort and Christianson (1981) distinguish strength of preferences for public service provision among rural residents. As they note, conflict exists because urban voters typically pay for below-capacity or inefficient rural hospitals through taxes or insurance premiums. 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. Thus emerges a thematic development acknowledging geographic dependence.

Another thematic development on political action committee (so-called PAC) contributions soon arose. 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. He estimates a system describing union PAC contributions and the AFL-CIO pro-union rating for each candidate. In the equation explaining pro-union rating, Wilhite includes geographic-specific data on unionization; respectively, whether the state is right-to-work, the district's or state's prior Republican presidential vote percentage, and whether the state or district receives direct benefits from the legislation the AFL-CIO uses in establishing its ratings. 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 proportion 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. 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, respectively, the Heckscher–Ohlin, Stolper–Samuelson, and Ricardo–Viner theorems. He includes legislator variables as well as district-level demographic and economic data, industry and occupation data including percent of the constituency involved in farming, and dummy variables indicating the presence of industries that are expected to benefit or be harmed by NAFTA. His results show that geographic and constituent interests strongly influence legislator voting and can sometimes outweigh partisan interests.

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 illustrates the potential rewards abounding from deeper methodological inquiry. They analyze the simultaneous interactions between congressional votes on sugar programmes and contributions from both pro- and anti-sugar PACs. Beneficiaries of sugar policy are few; there are fewer than 10,000 growers nationwide, with five corporations producing 90% of Hawaii's cane and two producing half of Florida's. The beneficiaries reap large rewards, because the domestic price from 1985-92 was almost two and a half times the world price and import quotas guaranteed US growers 85% of US sugar consumption. Sugar policy imposes large losses; the GAO estimates that consumers pay $2.50 for every dollar transferred to sugar producers. The authors employ a simultaneous equation system, with a voting equation and a pro- and anti-sugar contribution equation. Independent variables in the voting equation include the endogenous proand anti-sugar PAC contributions, and the exogenous variables include contributions from PACs for other commodities to measure logrolling, value of sugar produced in the legislator's district, agriculture committee membership, and ideology (the Americans for Democratic Action (ADA) rating). In the contribution equations independent variables include the endogenous propensity of the legislator to vote in the PAC's favor and contributions of the opposing PACs, exogenous variables of the legislator's margin of victory in the last election, seniority, committee membership, and ADA rating. In the pro-sugar equation the number of sugar farms is also included, and in the anti-sugar equation the rural-urban population ratio is used as a proxy for artificial sweeteners. 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. Another interesting result is that anti-sugar PACs tend to contribute more generally, even to pro-sugar legislators, while pro-sugar PACs contribute more narrowly to supporters. Evidence is found that PACs react to contribution competition, donating more as the opposition's donations rise. Membership on an agriculture committee does not significantly affect a legislator's vote due to the presence of so many 'yes' votes from the much larger group of non-committee members. Results are mixed for the other independent variables. The descriptive statistics show, *inter-alia*, that anti-sugar PACs contribute much less to the relevant legislators, and are more general in deciding to whom to donate. This fact seems to affect their results, where the implications for pro-sugar PACs have a sounder base in the empirical results than the implications for the anti-sugar PACs. The authors conclude that PACs contribute not to aid the election of sympathetic legislators, but to obtain favors in terms of policy votes or to ensure future support. Interests on both sides of the debate are influential in contributing, though their efforts and successes differ.

Following Brooks, Cameron, and Carter (1998), several fundamentally relevant contributions appear outside of the realm of agriculture. 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. Additional contributions, such as Jenkins and Weidenmier (1999) and Calcagno and Jackson (1998), for example, have focused elsewhere, taking less explicit account of geography in explaining Congressional voting patterns.

Importantly, Grossman and Helpman (2005) address the issue that national political parties have a set of policy objectives that they promote during campaigns, but that elected members of those parties do not have to abide by such objectives once in office but will, rather, obey more parochial concerns (especially given the strength of particular industries within one's district that are affected by legislation). If the party has an increased ability to punish legislators who do this, then the amount of deviation between what-was-campaigned-on and what-was-done-in-office by a particular legislator is reduced (a reduction in the so-called 'commitment problem'). Because the deviation is rarely zero, however, protectionist policies get passed (i.e., are supported by legislators) in districts populated by benefitting industries, and this is true even if national parties campaign on free trade in order to win votes. From a spatial perspective, the authors note that the "protectionist bias results whenever districts differ in their ownership shares of the industry-specific factors … As we shall see, the geographic distribution of the industry-specific factors also plays a central role (p. 1240)." The role of geography, though, is limited to allowing industry strength to differ between districts; the authors do not consider whether the degree of industry strength in a neighboring district influences the degree of the home-district legislator's support of protectionism. The presumption is that the costs and benefits and the bias stays within the district; e.g. if my district has a lot of sugar farmers, I would support a sugar tariff even if my party supports free trade and I campaigned on free trade. However, without explicit spatial estimation we cannot test whether the bias persists or increases and under what set of circumstances this may occur. The issue, then, appears to be 'whether or not neighbours, even without their own vested interest constituents, are influenced by the vested interests of their neighbours (reflecting the fact that socio-economic inter-relationships do not obey constitutional boundaries). The authors analyze, qualitatively, whether individual legislators are more concerned with their own constituents than with party platforms. The authors assume that 'constituents' are strictly limited to being within the legislator's district. However, it seems desirable to test whether the 'constituents' affecting a legislator's vote include people or industries in neighbouring districts.

Anderson, Rausser, and Swinnen, (2013) consider the impacts of protectionist biases and note, in particular: "In 2004, existing agricultural and trade policies accounted for an estimated 70 percent of the global welfare cost of all merchandise trade distortions, even though the agricultural sector contributes only 6 percent of global trade and 3 percent of global GDP." The protectionist biases referenced have significant and disproportional, detrimental effects on food prices, poverty, and income inequality. Some interesting observations emerge. Some reforms have been attempted but have not kept pace with advances and globalization in non-agricultural industries. Distortions, even within a country, are not consistent among different products or sectors. Distortions become largest in response to exogenous price shocks as policy attempts to insulate domestic agriculture from world price fluctuations. There is a strong anti-free trade bias with agricultural policy. Further, the authors cite research showing that, as the number of farmers decreases, resistance to supporting them via distortionary trade policies shrinks, and therefore the distortions themselves increase. But spatial concerns are left totally unaccounted. The authors suggest that a research question remains as to why, given that regions of countries show some similarities in terms of distortionary policies, particular countries within a region show dissimilarities. Perhaps an appropriately crafted spatial investigation might shed light on this important question?

Finally, and more recently, Olper and Raimondi (2013), consider the effects of different electoral rules and reach similar conclusions to Anderson, Rausser and Swinnen (2013). Proportional and presidential (first-past-the-post) democracies – compared to majoritarian and parliamentary democracies – are associated with more public support for agricultural interests (who, as a small group, are more likely organized as a special interest). They find less support to food consumers (who, as a large group or majority of the population, are less politically organized), and the size of the effect is larger for import-competitive sectors (vs. export sectors) and staple foods (vs. food mainly destined for export). But how would the conclusions be affected by the infusion of spatial interaction among the various trade actors under consideration?

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 general neglect of possibilities for spatial externalities in voting, considerations in geo-political-preference support and consequent impacts on policy. These limitations motivate our empirical inquiry.

3. Modeling Voting Behaviour

In order to link vote behaviour to a spatial externality, consider voting to be the observed outcome of a process in which regional constituency, 'spatial contiguity,' and other factors affect vote outcomes. Formalizing, consider the relationship

(1) $$z_i = \rho\, \mathbf{w}_{-i}'\mathbf{z}_{-i} + \mathbf{x}_i'\boldsymbol{\beta} + \varepsilon_i,$$

where i = 1, 2, .., N denotes a congressional voting district; z_i, an element of the N-vector $\mathbf{z} \equiv (z_1, z_2, .., z_N)'$, is the propensity of the representative (of the constituency as determined by the congressional district) to vote in a particular way in district 'i'; parameter $\rho \in (\underline{\rho}, \overline{\rho})$, a scalar, depicts the magnitude of spatial correlation in vote propensities; $\mathbf{w}_{-i}$ is the ((N-1)×1) vector of binary elements of $\mathbf{w}_i \equiv (w_{i1}, w_{i2}, .., w_{iN})'$, in which $w_{ij} = 1$ if i and j are 'neighbours' and $w_{ij} = 0$, otherwise, excluding w_{ii}; $\mathbf{z}_{-i}$ denotes the ((N-1)×1) vector of latent responses obtained by deleting the i^{th} element of $\mathbf{z}$; $\mathbf{x}_i \equiv (x_{i1}, x_{i2}, .., x_{iK})'$ denotes a K-vector of covariates conditioning the latent response; $\boldsymbol{\beta} \equiv (\beta_1, \beta_2, .., \beta_K)'$ denotes the corresponding K-vector of response coefficients; and ε_i denotes a standard-normal random variable. In the remainder we maintain the assumptions that ε_i is normally distributed with zero mean and unit variance and that the bounds on the spatial correlation, $(\underline{\rho}, \overline{\rho})$, conform to the usual eigenvalue conditions (Anselin, 1988). Some additional notation will prove useful. Throughout, we use the convention that $f^a(b|c,d,..,e)$ denotes a type-*a* *probability distribution function* (pdf) for random variable *b* conditioned by the values of parameters *c*, *d*, .., and *e*. Hence, ε_i has distribution $f^N(\varepsilon_i|0,1)$. The unit-variance restriction is the standard assumption required for identification in the probit model (see, for example, Greene 2003, p. 669). The normality assumption is a useful approximation which, in the absence of other motivating evidence, seems reasonable to apply. We observe data $\{\mathbf{x}_i, \mathbf{w}_i, y_i\}_{i=1}^N$ where $y_i = 1$ if the congressional vote in district i is a 'yea;' observe $y_i = 0$ otherwise; and make inferences about $\boldsymbol{\theta} \equiv (\boldsymbol{\beta}', \rho)'$. Stacking observations in (1),

(2) $$\mathbf{z} = \rho\mathbf{W}\mathbf{z} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}.$$

where $\mathbf{W} \equiv (\mathbf{w}_1, \mathbf{w}_2, .., \mathbf{w}_N)$ denotes the N-dimensional, square, symmetric matrix of binary contiguity indicators; $\mathbf{X} \equiv (\mathbf{x}_1, \mathbf{x}_2, .., \mathbf{x}_N)'$ denotes an N×K matrix of observations on the covariates; and $\boldsymbol{\varepsilon} \equiv (\varepsilon_1, \varepsilon_2, .., \varepsilon_N)'$ denotes an N-vector of disturbances with distribution $f^N(\boldsymbol{\varepsilon}|\mathbf{0}_N,\mathbf{I}_N)$. Here $\mathbf{0}_N$ is the length-N null vector and $\mathbf{I}_N$ is the N-dimensional identity matrix.

Bayesian estimation is complicated by the presence of correlation across observations, which is jointly manifested by the correlation parameter ρ and the design of the spatial contiguity matrix $\mathbf{W}$. The conventional (non-spatial) probit model is nested as a special case of (2) whenever $\rho = 0$. Albert and Chib (1993) present an algorithm for posterior inference for the conventional probit model and LeSage (2000) extends their work to incorporate the spatial externality. We emphasize the two-part nature of the spatial externality, namely the magnitude of the correlation, manifested by ρ, and the design of the spatial contiguity, $\mathbf{W}$. A heritage in applied adoption studies in agricultural and development economics, many of which are relevant in the present context, constructs $\mathbf{W}$ by setting elements $w_{ij} = 1$ if observations i and j are ‘neighbours’ and $w_{ij} = 0$ otherwise; and proceeds, conditionally, to estimate ρ. Case (1992) provides an example in agriculture and many others exist. The point that needs emphasis here is that usually, though not always, the definition of the ‘neighbourhood’ and thus the ‘span’ of the contiguity regions selected by the investigator are *arbitrary*. Yet, this choice has important ramifications for most of the policy implications drawn from formal analysis. Consequently, we seek inferences about two important components: the magnitude of ρ; the exact design of $\mathbf{W}$.

We define five, respective, contiguity matrices, where each alternative is related to another in a sequential expansion of the region of neighbourhood impacts. In the first model, which we denote $\mathbf{M}_1$, the contiguity matrix $\mathbf{W}^{(1)}$, is defined by $w_{ij} = 1$ if observations ‘i’ and ‘j’ reside in neighbouring congressional districts, which are the fundamental units of analysis. Next, we define $\mathbf{M}_2$ to correspond to $\mathbf{W}^{(2)}$, which adds those districts that are contiguous with the current ones (i and j). Continuing sequentially, the fifth model exhausts the entire sample, combining it into one single ‘neighbourhood.’ Thus, model selection centres on the five consecutive specifications of (2) where $\mathbf{W}^{(j)}$, j = 1, 2, .., 5, denote the respective designs. It will also be useful to refer to the model in which no account is taken of spatial dependence. This specification is, the ‘conventional probit model’ which we refer to as the ‘null-spatial-weight model’ $\mathbf{W}^{(0)}$. Consequently, $\mathbf{W}^{(j)}$, j = 0, 1, 2, .., 5, define six mutually exclusive and exhaustive delineations of the sample space. Assessing and comparing formally the statistical evidence in favour of each competing formulation is a major contribution of the exercise, and provides an answer, supported formally by statistical evidence, to the question: How large is congressional dependence (i.e., its ‘span’ or ‘scope’)?

Algorithms for comparing the competing formulations are presented in Chib (1995) and Chib and Jeliazkov (2001) and an introduction to the ideas underlying the Markov Chain Monte Carlo

(MCMC) theory is presented in Gelfand and Smith (1990), Casella and George (1992) and Chib and Greenberg (1995). Problematic is the need to employ a proper prior.

Although the prior information concerning the alternative specifications is relatively diffuse, we present derivations in terms of the proper prior $\pi(\boldsymbol{\theta}) \equiv f^N(\beta|\hat{\beta}_o, C_{\beta o}) \times f^N(\rho|\hat{\rho}_o, C_{\rho o})$, which is the product of a multivariate-normal distribution for the response coefficients and a normal distribution for the spatial correlation. We implement the prior using parameter values $\beta_o = \mathbf{0}_K$, $C_{\beta o} = I_K \times 5$, $\rho_o = 0$, and $C_{\rho o} = 5$. Given these values, inference is conducted with respect to the joint posterior distribution for the parameters, which is proportional to the likelihood for the data and the prior, namely $\pi(\boldsymbol{\theta}|\mathbf{y}) \propto f(\boldsymbol{\theta}|\mathbf{y}) \times \pi(\boldsymbol{\theta}|\mathbf{y})$.

For pedagogic purposes, we first outline the steps required to implement conventional probit estimation; the spatial probit is then a straightforward extension.

With respect to conventional probit estimation, the likelihood, $f(\boldsymbol{\theta}|\mathbf{y}) \equiv \prod_{i=1}^{N} \Phi(-\mathbf{x}_i'\boldsymbol{\beta})^{1-y_i} \times \Phi(\mathbf{x}_i'\boldsymbol{\beta})^{y_i}$, is complicated by the presence of the integrals implicit in the cumulative standard-normal distribution functions $\Phi(-\mathbf{x}_i'\boldsymbol{\beta})$, and $\Phi(\mathbf{x}_i'\boldsymbol{\beta})$, i = 1, 2, .., N, respectively. However, Albert and Chib (1993) show that these problems are easily circumvented, by augmenting the observed data likelihood $f(\boldsymbol{\theta}|y)$ with the latent responses, $\mathbf{z}$, and, instead, focusing attention on the complete data likelihood $f(\boldsymbol{\theta}|\mathbf{y},\mathbf{z}) \equiv f^N(\mathbf{z}|\mathbf{X}\boldsymbol{\beta},\mathbf{I}_N)$. This formulation proves tractable because, even though we do not observe the latent $\mathbf{z}$, its components can be efficiently estimated, given values for the unobserved elements in the coefficient vector, $\boldsymbol{\beta}$. In this context, iterating sequentially between the two full conditional distributions comprising the joint posterior leads to iterations that simulate draws from the marginal distributions that we seek. The conditional distributions for $\boldsymbol{\beta}$ and $\mathbf{z}$ are, respectively

(3) $\boldsymbol{\beta}|\mathbf{z} \sim f^{N}(\boldsymbol{\beta}|\hat{\boldsymbol{\beta}}, \mathbf{C}_{\boldsymbol{\beta}})$,

where $\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X} + \mathbf{C}_{\boldsymbol{\beta}o}^{-1})^{-1} (\mathbf{X}'\mathbf{z} + \mathbf{C}_{\boldsymbol{\beta}o}^{-1}\hat{\boldsymbol{\beta}}_o)$ and $\mathbf{C}_{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X} + \mathbf{C}_{\boldsymbol{\beta}o}^{-1})^{-1}$; and

(4) $\mathbf{z}|\boldsymbol{\beta} \sim f^{TN}(\mathbf{z}|\hat{\mathbf{z}}, \mathbf{C}_{\mathbf{z}}, \mathbf{y})$,

where $\hat{\mathbf{z}} = \mathbf{X}\boldsymbol{\beta}$, $\mathbf{C}_{\mathbf{z}} = I_N$, and, for i = 1, 2, .., N, $z_i \leq 0$ if $y_i = 0$, and $z_i > 0$, otherwise. Efficient one-for-one draws are obtained by exploiting the probability integral transform (Mood, Graybill, and Boes 1974, pp. 202-3). Consequently, given a vector of arbitrary starting values, say $\mathbf{z} = \mathbf{z}^{(0)}$, efficient estimation of the conventional probit model is obtained by iterating the algorithm:

$\mathbf{A_1}$: Draw $\boldsymbol{\beta}^{(g)}$ from (3). Draw $\mathbf{z}^{(g)}$ from (4).

Posterior inference is then conducted using the sample $\{\boldsymbol{\beta}^{(g)}, \mathbf{z}^{(g)}\}_{g=1}^{G}$ which is obtained by iterating $\mathbf{A_1}$ a total of G times, once a 'burn-in' – a point beyond which convergence is attained – is located.

In order to compare the evidence in favour of the conventional probit model against the alternative spatial probit specification, we need to compute the 'marginal likelihood' corresponding to each model. In the case of the standard probit, an efficient algorithm is presented in Chib (1995). It is implemented simply by running the algorithm $\mathbf{A_1}$ one additional time with the parameters $\boldsymbol{\beta}$ set at some high-density value, say $\boldsymbol{\beta} = \boldsymbol{\beta}^*$ ($\equiv \boldsymbol{\theta}^*$) and collecting an estimate of the posterior distribution for $\boldsymbol{\beta}$, leading to the estimate (on the computationally convenient log scale), $\ln m(\mathbf{y}) = \ln f(\boldsymbol{\theta}^*|\mathbf{y}) + \ln \pi(\boldsymbol{\theta}^*) - \ln \pi(\boldsymbol{\theta}^*|\mathbf{y})$. The first two components on the right-hand side are available by direct calculation but the third, in general, must be estimated. We estimate it from the reduced run by computing, $\pi(\boldsymbol{\theta}^*|\mathbf{y}) \cong G^{-1} \sum_g \pi(\boldsymbol{\theta}^*|\mathbf{y}, \mathbf{z}^{(g)})$. At the end of this reduced run an estimate of the model marginal likelihood is available and an estimate of its standard error is also available (Newey and West , 1987).

Complications in the *spatial* probit are overcome by a straight-forward extension of the MCMC method. Specifically, by appending one additional step to the algorithm $\mathbf{A_1}$ we can derive estimates of the expanded parameter vector $\boldsymbol{\theta} \equiv (\boldsymbol{\beta}',\rho)'$. The appended step involves drawing a sequence of observations $\{\rho^{(g)}\}_{g=1}^{G}$ conditional on the draws for the remaining unknowns, respectively $\boldsymbol{\beta}$ and $\mathbf{z}$, and the basic algorithm, $\mathbf{A_1}$, is generalized in three ways. First, because the full conditional distribution for the correlation parameter is not available in closed form, the draw for ρ is made by implementing a random-walk Metropolis-Hastings step. This Markov Chain procedure is thoroughly explained in standard texts (see, Robert and Casella (1999) for background and LeSage (1997, 1999, 2000, 2002) and Holloway, Shankar, and Rahman (2002) for demonstrations).

A second complication arises due to the fact that, under the assumption $\rho \neq 0$, the individual draws for each component of $\mathbf{z}$ are conditionally correlated, rendering problematic derivation of the full set of latent responses. This problem is discussed in detail in Geweke (1994), where it is suggested that each of the draws in $\mathbf{z}$ must be made sequentially. Finally, a few modifications to the full conditional distributions in (3) and (4) are required by the fact that the response model now contains the binary-weights matrix, $\mathbf{W}$. The conditional draws for $\boldsymbol{\beta}$ and $\mathbf{z}$ are, respectively

(5) $\boldsymbol{\beta}|\mathbf{z},\rho \sim f^{N}(\boldsymbol{\beta}|\hat{\boldsymbol{\beta}},\mathbf{C}_{\boldsymbol{\beta}})$,

where $\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X}+\mathbf{C}_{\boldsymbol{\beta}o}^{-1})^{-1}(\mathbf{X}'\mathbf{A}\mathbf{z}+\mathbf{C}_{\boldsymbol{\beta}o}^{-1}\hat{\boldsymbol{\beta}}_o)$, $\mathbf{A} = \mathbf{I}_N-\rho\mathbf{W}$ and $\mathbf{C}_{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X}+\mathbf{C}_{\boldsymbol{\beta}o}^{-1})^{-1}$; and

(6) $z_i|\boldsymbol{\beta},\rho \sim f^{tN}(z_i|\hat{\mathbf{z}}_i,C_{zi},\mathbf{y})$, i = 1, 2, .., N,

where $\hat{\mathbf{z}}_i = \mathbf{A}^{-1}\mathbf{x}_i'\boldsymbol{\beta} - V_{ii}^{-1}\mathbf{V}_{i\text{-}i}(\mathbf{z}_{\text{-}i}-\mathbf{X}_{\text{-}i}\boldsymbol{\beta})$; $\mathbf{V} = \mathbf{A}'\mathbf{A}$; V_{ii} denotes the scalar appearing in the i^{th} row and column of $\mathbf{V}$; $\mathbf{V}_{i\text{-}i}$ denotes the (N-1)-dimensional row vector obtained by deleting the i^{th}

column from the i^{th} row of $\mathbf{V}$; and the variance of the i^{th} latent response is $C_{zi} = V_{ii}^{-1}$. Third, the conditional distribution of ρ is proportional to

$$(7) \qquad \rho|\boldsymbol{\beta},\mathbf{z} \;\sim\; |\mathbf{A}| \exp\{-.5(\mathbf{Az}-\mathbf{X}\boldsymbol{\beta})'(\mathbf{Az}-\mathbf{X}\boldsymbol{\beta})\} \times \exp\{-.5(\rho-\hat{\rho}_o)'C_{\rho o}^{-1}(\rho-\hat{\rho}_o)'\} \equiv \kappa(\rho|\boldsymbol{\beta},\mathbf{z}),$$

which has an unknown integrating constant. The corresponding Metropolis step involves drawing a proposal, $\tau \sim f^N(\tau|\rho,\zeta)$, accepting the draw with probability

$$(8) \qquad \alpha(\rho,\tau) \equiv \min\{\kappa(\tau|\boldsymbol{\beta},\mathbf{z}) \div \kappa(\rho|\boldsymbol{\beta},\mathbf{z}),1\},$$

and adjusting endogenously the variance parameter, ζ, in order to target an acceptance rate of 25% of the total draws. Experiments with simulated data suggest that an acceptance rate of about 25% is highly satisfactory.

In summary, given arbitrary starting values, $\mathbf{z} = \mathbf{z}^{(0)}$, efficient estimates of the spatial probit model are obtained by iterating

> $\mathbf{A_2}$: Draw $\boldsymbol{\beta}^{(g)}$ from (5). Draw $\mathbf{z}^{(g)}$ from (6). Draw $\tau^{(g)}$ from $\tau \sim f^N(\tau|\rho,\zeta)$ and set $\rho^{(g)} = \tau^{(g)}$ with probability (8).

Finally, the model's marginal likelihood, m($\mathbf{y}$), is estimated by running the algorithm an additional two times with $\boldsymbol{\beta}$ and then ρ set at their high-density values, $\boldsymbol{\beta}^*$ and ρ^*, respectively. Additional details are presented in Jeliazkov and Chib (2001). At the end of the reduced runs of $\mathbf{A_1}$ and $\mathbf{A_2}$ we are able to conduct posterior inference and determine whether a spatial externality in vote dependence exists; its location; its scale; and its span.

4. Data

The legislation under consideration is the conference report HR 2646 arising in the second session of the 107^{th} Congress (which met in 2001 through 2002). Data on this legislation was most conveniently available for this study, though the methods can clearly be applied to other legislation, perhaps of richer character. 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 website,[1] 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 website.[2] 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.'

In order to measure political influence, we collect data on whether the legislator was an incumbent and the popular support the legislator received in his most recent election. The *INCUMBENT* and *WINLAST* variables are derived from the Federal Elections Commission. Data for the Representatives relate to the 2000 election.[3] The *WINLAST* variable is the percentage of the general election popular vote received by the candidate within their district. We also 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 the continuous variable *LQ2001* for each observation. These variables represent the 'Liberal Quotient' determined by Americans for Democratic Action, Inc. (ADA), and correspond to the LQ score the legislator received from the ADA in 2001, covering the 107th Congress.[4]

We include control variables to measure the influence of agricultural interests in the legislator's district. The variable *FARMEMPLOYUSDA* represents the percentage of state employment in farm or farm-related occupations, taken from the Economic Research Service of the U.S. Department of Agriculture (USDA).[5] For the Representatives, we obtain the percentage of a state's population residing in each Congressional district using data from the Census Bureau.[6] We then multiply this by the state's *FARMEMPLOYUSDA* to get district percent employment in farming. 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 the Census 2000 Summary File 1 for each Congressional District.[7]

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 Congress.[8] For each member, we create the variable *AGPAC* as the proportion of the representative's total PAC contributions accounted for by 'agribusiness' PACs during the 2001-2 period. This variable proxies for the *relative significance of agricultural PACs* in the member's portfolio. 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 Agriculture.[9] The variable *MVP* (market value of payments) is the average market value of production per farm in dollars and is intended to measure the relative size and influence of farms, relative to the non-agrarian economy, in a Congressional district. By averaging across the number of farms within the Congressional district, the variable proxies the average or 'public' impacts of payments. 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, and the averaging conveys better the notion of 'public' versus 'private' 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. Prior to estimation all covariates are normalized by their maximum values.

5. Empirical Results

In presenting results, we focus on the preferred specification that emerges from the model-selection exercise. Table 1 presents the results of the models comparisons. The first column in table 1 indicates the model in question. We estimate two versions of the models, namely one, which we refer to as 'specification one,' that excludes a constant term; and another, which we refer to as 'specification two,' in which the constant is included. We refer to these formulations using the slightly modified notation $\mathbf{W}^{(i,j)}$, wherein 'i' denotes 'specification' and 'j' denotes the 'spatial-weight model.' These indications appear in column one in table 1. The second column reports the estimate of the log-likelihood evaluated at the high density point. The third column reports the logarithm of the marginal likelihood evaluated at the high density point. The fourth column reports the numerical standard error of the log-marginal likelihood estimate. The fifth, sixth and seventh columns report, respectively, and where available, the lower (2.5%) limit of the 95% highest posterior density interval for 'rho', the posterior mean estimate of rho and the upper

(97.5%) limit of the 95% highest posterior density interval for 'rho.' And in column eight we report the implied posterior probabilities across the twelve-dimensional (the Cartesian product of 'specifications' ⊗ 'models') model space.

(Insert table 1 about here.)

Several points are noteworthy. First, the high density point adopted is the posterior means of the parameters. Second, and, perhaps most importantly, neither the likelihood values nor the marginal likelihood values indicate that there exists a clearly dominant model. In particular, the rankings of the maximized and the estimated likelihood values diverge; both are different from the rankings obtained from comparing marginal likelihood values. Third, we observe a fairly sizable difference between the marginalized and the estimated likelihood values, indicating that the prior information is relatively influential in the model assessment exercise. Fourth, the posterior mean for ρ generated by each of the models in question varies substantially across the model space. Hence we deem it most important to identify the clearly dominant model, should one exist. There are, in fact, three dominant models, namely $\mathbf{W}^{(1,1)}$, a single-neighborhood specification in which the constant is excluded; $\mathbf{W}^{(2,0)}$, a null-neighborhood specification in which the constant is included; and, third, $\mathbf{W}^{(2,1)}$ a single-neighborhood specification in which the constant is included. We note, additionally, that the implied probabilities of these three separate specifications across the model space (namely 0.26, 0.12, 0.62) is exhaustive, summing to 1.00, net of rounding. Thus, in further evaluation, we disregard the remaining models focusing our attentions on these three respective formulations. We note further that one of the specifications ($\mathbf{W}^{(2,1))}$ is at least twice as likely to have generated the data as the other two. We therefore focus on the formulation $\mathbf{W}^{(2,1)}$ as the benchmark when discussing parameter estimates and marginal effects.

Still, probability masses of 0.26 and 0.12 are considered too large to ignore and given the added uncertainty that their presence creates, we conduct inference by combining estimates derived from each of the three candidate models, which Bayesians refer to as *model averaging*.

Model averaging is advisable in many situations, but is particularly relevant in cases where the data fail to favour a single specification. The manner in which we combine model estimates is straightforward, but the conceptual underpinnings of the procedure are deep. Examples of model averaging in agricultural economics are scarce, with one notable exception (Chua, Griffiths, and O'Donnell, 2001). Early work dates at least to Min and Zellner (1990) and to Palm and Zellner (1992). Since then numerous contributions appear and a selection that we find particularly insightful, include Draper (1995); Raftery, Madigan, and Volinsky (1995); Clyde (1999a, 1999b, 2000); Fernàndez, Ley, and Steel (2001a, 2001b); Hoeting, Raftery, and Madigan (1999, 2002); and Viallefont, Raftery, and Richardson (2001).

A good introduction to Bayesian model averaging is presented in Koop (2003, pp. 265-282). Given a quantity of interest, say $g(\boldsymbol{\theta})$, we estimate its posterior distribution using a weighted sum of the probabilities in favor of each model under consideration. To perform this calculation we use the marginalized likelihoods computed in the previous section, exponentiate each one (they are estimated in natural logarithms), and place them in the formula

(9) $$f(g(\boldsymbol{\theta})|\mathbf{y}) = \sum_j w_j\, f(g(\boldsymbol{\theta})|\mathbf{y},m_j),$$

where the weights are $w_j \equiv \wp_j \exp\{\log m(\mathbf{y}|m_j)\} \div \sum_j \wp_j \exp\{\log m(\mathbf{y}|m_j)\}$ and the $\wp_j$ are prior probabilities satisfying the restriction $\sum \wp_j = 1$.

The over-arching metric of the analysis is the posterior distribution of the correlation parameter. Figure 1 reports this distribution. The distribution has a slightly elongated tail to the left, but the overwhelming bulk of the draws reside on the positive real line. Thus, we conclude with confidence that the impact of the spatial externality is positive. And we note also that the location and scale of the spatial lag parameter, ρ, shows that there is a spatial relationship between congressional districts and their vote behaviour, which confirms Thorbecke's (1997) observation that Representatives are responsive to their geographic interests.

(Insert figure 1 about here.)

Table 2 presents reports of posterior means of the parameter distributions. For the purpose of comparison, we present the estimates corresponding to the spatial-probit formulation $\mathbf{W}^{(2,1)}$ and compare them to those under the conventional-probit specification, which, inclusive of the constant, is $\mathbf{W}^{(2,0)}$. The first column lists the variable names; the second, third and fourth columns present posterior mean estimates of the spatial probit parameters, with 95% highest posterior density (HPD) intervals in parentheses; and the fifth, sixth and seventh columns present estimates of the conventional probit parameters, with 95% highest posterior density (HPD) intervals in parentheses. Only the HPD intervals corresponding to *AGPAC* and *URBAN* do not contain zero. This result is consistent across the two formulations. The positive coefficient for *AGPAC* indicates that there is a positive relationship between agricultural PAC contributions and the actions of legislators, which is in accordance with the idea that legislators are responsive to constituent interests. The *URBAN* variable is also deemed to be a determinant of legislator activity given the bounds of the HPD interval, but the association is negative. Congresspersons from urban areas tend to not support agricultural legislation presumably because 1) their districts contain little, if any, agricultural activity, and 2) subsidies for farming activities are viewed as hurting their constituents who must pay more for items such as milk and sugar, as well as other 'necessities.'

Comparing results obtained for the spatial probit formulation (columns two, three and four) with those derived for the conventional probit model (columns five, six and seven), some small but potentially important differences emerge in both the locations and the scales of the posterior distributions.

These differences draw into question the magnitude of policy inferences that investigators draw from the respective exercises and raise demand for further examination. These small but noteworthy differences between the two models are further confirmed with reference to the marginal effects estimates, which depict the impacts on the probabilities of achieving a 'yea' vote in response to changes in the covariates. These estimates are reported in table 3. In particular the marginal effects estimates indicate some important differences across both the spatial-probit with nearest-neighbour contiguity (columns two, three and four), $\mathbf{W}^{(2,1)}$; and the non-spatial, conventional probit formulation (columns five, six and seven), $\mathbf{W}^{(2,0)}$. With reference, momentarily, to the spatial probit, the significance in parameter estimates of the covariates *AGPAC* and *URBAN* is now also exhibited by *FARMEPLOYUSDA, DEMOCRAT, WINLAST, AGCOM*, *MVP*, and *ADA*; while, in contrast, the conventional probit only uniquely identifies *AGPAC* and *URBAN* as with the mean effects. Importantly, the potency of *AGPAC* response between the two formulations is quite different, with the scale of impact substantially larger under the preferred, spatial-probit, formulation. These estimates clearly indicate that increases in PAC contributions generate 'yeas' within the House. However, the precise impacts of these contributions across the complete sample space remain uncertain. Thus scope arises for experimentation.

(Insert table 3 about here).

Focusing on the increase in scale of PAC contributions that is required, according to these estimates, to ensure full compliance (a unanimous 'yea' vote across the sample), we consider the question of depicting differing patterns of influence across the alternative neighbourhood specifications. Using the preferred formulation, $\mathbf{W}^{(2,1)}$, as the benchmark against which to depict alternatives, we consider the pattern of adjustments corresponding to the non-spatial probit $\mathbf{W}^{(2,0)}$, and the remaining, spatial-probit configurations, $\mathbf{W}^{(2,2)}$, $\mathbf{W}^{(2,3)}$, $\mathbf{W}^{(2,4)}$, and $\mathbf{W}^{(2,5)}$, where, instead of the posterior means estimates for 'rho' obtained under each formulation, we use the correlation mean reported under the preferred specification, namely, $\mathbf{W}^{(2,1)}$. The reason we do this is simple. Conditioning upon a given correlation value but adjusting, *ceteris paribus*, only the neighbourhood 'treatments,' serves to emphasize the 'range' or the 'scope' of reach of the spatial externality influencing vote behaviour. And it is this significant aspect of the voting externality the investigators have largely ignored. Hence, these experiments are significant in the extent that they are almost surely the first of their kind within an agricultural-legislation-vote setting. We conjecture also, that they may be seminal within the broader regional-economic and spatial-econometric literatures.

Figure 2 presents the results of the policy experiment of increasing PAC contributions across the sample. The vertical axis reports the number of 'yea' votes and the horizontal axis reports the increments by which the PAC contributions must be altered in order to attain the outcome. There is a noteworthy difference in the responsiveness of 'yea' votes to these increases across the separate formulations and the rate of increase in 'yea' votes per unit increase in PAC contributions is different across the respective formulations. Not only is the scale and location of the spatial correlation important, but it is considerably magnified by the extent to which a given correlation attains 'reach' throughout the sample. And this latter aspect has been ignored to date.

Our results suggest that such neglect may significantly bias inferences and post sample policy predictions. To the extent that the social-scientific laboratory used for our experiments exemplifies a wide and broader set of circumstances, such neglect is, likely, quite significant.

(Insert figure 2 about here.)

6. Concluding Comments

We examine the hypothesis, hitherto neglected in the political-economy-of-agriculture literature, that Congressional votes are spatially correlated. Using recent advances in Bayesian computation, our spatial probit model highlights salient differences between it and the results obtained from conventional probit estimation. We have made considerable effort to emphasize that whenever a spatial externality is observed there are two important dimensions to its 'nature.' One, which is typical of the empirical econometric literature, is the sign and magnitude of the spatial externality. The other, which we claim has been largely ignored, is the geographic 'scope' or 'range' of the spatial externality. We have shown in this paper, using a set of robust Bayesian procedures, that both the scales and the scopes of the spatial externality are identifiable, are estimable and are implementable in posterior predictive settings. We argue that such settings – hitherto ignored by agricultural economists – are important.

This basic methodology could be extended in at least two directions in order to obtain nuanced insights into spatial externalities. First, the nature of the findings here should be assessed in a wide and varied set of circumstances, including other spatially relevant data generating environments. The one we have chosen is the one most convenient and, perhaps relevant to our audience, but others abound.

Second, with reference to PAC contributions in particular, but previous work in general, especially Baldwin and Magee (2000) and similar, one could consider PACs that may 'mitigate' or are likely to support a ‘nay’ vote, though it may be difficult to identify such ‘nay’ PACs. Experience suggests that, while farmers and agribusinesses would support distortionary policies, those opposing them would be the much broader group of food consumers, who don’t have a realistic PAC to speak for them. While the pro-Farm-Bill PAC is easier to identify, anti-Farm-Bill PACs are more difficult to identify. For example, given the propensity of some United States legislation to contain ‘incentives’ to persuade opponents to sign up to ‘bills,’ identifying negative PACs and quantifying their impacts may be impossible. Thus, further PAC related work should perhaps devote effort to diversifying the makeup of the potential covariates pool.

Finally we emphasize aspects of the Bayesian procedures, which are particularly useful in our setting. One advantage, of Bayesian inference, is the marginalization of extraneous information – other than the data – from focal quantities. Specifically, the important posterior distribution identified in figure 1 is *not conditional on the values of other parameters* within the model. Other quantities, useful in estimation, but extraneous to interpretation, have been integrated out of proceedings (if not analytically and exactly in closed form, then, at least, approximately and numerically), which, of course, is desirable. This feature – an over-arching facet of all Bayesian investigations – is rarely emphasized despite its obvious advantages.

A second attractive feature of our approach is its ability to accommodate uncertainty about alternative models. In the present setting we specify and examine twelve different versions, and it appears from the data that three have substantial support. The Bayesian paradigm provides a coherent set of formulae with which to combine the respective models, on the basis of the statistical support for each element, across all of the available alternatives, comprising the conditional model space. Here we use these methods to make robust assessments of the likely scale and scope of an important spatial externality and focus attention on a hitherto ignored aspect of the social experiment. We have shown this to be significant.

Third, because the data and parameters are unified in a coherent joint probability distribution function through a set of rational and consistent principles, we are able to derive, *a posteriori*, predictions, as one would in sampling-theoretic contexts, with one more desirable feature than is available there. Rather than point estimates about policy predictions, the *Bayes estimate* is contained within a full (marginal) probability distribution function characterizing support across the unknowns' space. In our example, the important unknown we examine is precisely the number of 'yea' votes arising in response to an increase in PAC contributions. The response functions depicted in figure 2 are posterior means of separate probability distributions, derived at each point within the experimental space. The distributions of the results of these experiments are derived without reference to extraneous parameters (which are removed from and by the estimation procedure) making the conclusions that we draw robust to concerns about the unknown values of other parameters within the systems.

These advantages, as usual, arrive at a cost, which is only sometimes significant. The nature of this cost and its implications for analysis lie beyond the scope of this paper, but are discussed principally in Jeffries (1961); somewhat loosely in Zellner (1996); more formally, from a mathematical perspective, in Berger (1984); from a formal, foundational viewpoint, in Bernardo and Smith (1994); and, recently, in an interview between O'Hagan and Lindley devoted to some of the contentions surrounding widespread use of the Bayesian approach to inference.[10]

Footnotes

1. http://clerk.house.gov/evs/2002/roll123.xml.

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

3. http://www.fec.gov/pubrec/fe2000/house.xls

4. http://www.fec.gov/pubrec/fe1998/98senate.htm

5. http://ers.usda.gov/Data/FarmandRelatedEmployment/

6. The “Fast Facts for Congress,” http://fastfacts.census.gov/home/cws/main.html, provide congressional district populations.

7. http://factfinder.census.gov/servlet/DTGeoSearchByListServlet?ds_name=DEC _2000_SF1_U&_lang=en&_ts=107886252515

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

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

10. http://www.youtube.com/watch?v=cgclGi8yEu4.

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Tables

Table 1. Marginal likelihood estimates.

Model	Log Likelihood	Log Marginal Likelihood	Numerical Standard Error	Rho 2.5% Lower Limit	Rho Posterior Mean	Rho 97.5% Upper Limit	Implied Posterior Model Probability
			Constant Excluded				
$\mathbf{W}^{(1,0)}$	-186.95	-194.21	0.32	-	-	-	0.00
$\mathbf{W}^{(1,1)}$	-171.37	-189.16	0.83	(0.26)	0.44	(0.62)	0.26
$\mathbf{W}^{(1,2)}$	-180.76	-198.00	0.74	(0.12)	0.41	(0.67)	0.00
$\mathbf{W}^{(1,3)}$	-183.65	-202.12	0.18	(-0.11)	0.46	(0.84)	0.00
$\mathbf{W}^{(1,4)}$	-185.14	-202.93	0.19	(-0.32)	0.48	(0.93)	0.00
$\mathbf{W}^{(1,5)}$	-186.19	-203.03	0.24	(-0.62)	0.31	(0.90)	0.00
			Constant Included				
$\mathbf{W}^{(2,0)}$	-181.93	-189.89	0.23	-	-	-	0.12
$\mathbf{W}^{(2,1)}$	-169.66	-188.27	1.25	(0.20)	0.41	(0.59)	0.62
$\mathbf{W}^{(2,2)}$	-178.56	-198.98	0.14	(-0.02)	0.30	(0.61)	0.00
$\mathbf{W}^{(2,3)}$	-180.83	-199.97	0.41	(-0.31)	0.24	(0.71)	0.00
$\mathbf{W}^{(2.4)}$	-182.09	-196.93	1.32	(-2.19)	-0.21	(0.84)	0.00
$\mathbf{W}^{(2,5)}$	-181.02	-197.31	0.70	(-6.04)	-2.76	(0.04)	0.00

Note: Log likelihood and log marginal likelihood values are reported at posterior means of the regression coefficients and of the correlation parameter. Estimates are based on a burn-in sample size of S = 100,000 and a Gibbs sample size of G = 100,000.

Table 2. Parameter estimates

Variable	Spatial Probit			Non-Spatial Probit		
Farm Employment USDA(FARMEMPLOYUSDA)	(-7.34)	-1.86	(3.31)	(-6.76)	-0.88	(5.73)
Incumbent Status(INCUMBENT)	(-0.75)	-0.19	(0.33)	(-0.69)	-0.15	(0.40)
Member of Democratic Party(DEMOCRAT)	(-1.07)	0.09	(1.13)	(-1.04)	0.15	(1.22)
Percent Agricultural PAC Money(AGPAC)	(0.97)	3.54	(6.24)	(1.35)	3.93	(6.55)
Urban Population %(URBAN)	(-3.09)	-2.20	(-1.19)	(-3.68)	-2.69	(-1.82)
Win Last Election %(WINLAST)	(-1.03)	0.33	(1.59)	(-0.95)	0.38	(1.69)
Member Agricultural Committee(AGCOM)	(-0.26)	0.44	(1.17)	(-0.20)	0.46	(1.15)
Market Value of Production(MVP)	(-21.31)	-4.76	(12.99)	(-24.16)	-7.50	(9.50)
Government Payments(GP)	(-17.27)	1.47	(18.89)	(-16.86)	1.07	(19.16)
ADA Score(LQ2001)	(-0.87)	0.37	(1.74)	(-1.04)	0.31	(1.84)
Constant	(0.31)	1.57	(2.80)	(0.74)	2.03	(3.34)

Note: Estimates are based on a burn-in sample size of S = 100,000 and a Gibbs sample size of G = 100,000. Ninety-five percent highest posterior density limits are reported in parentheses.

Table 3. Marginal effects estimates.

Variable	Spatial Probit			Non-Spatial Probit		
Farm Employment USDA(FARMEMPLOYUSDA)	(0.07)	1.46	(3.23)	(-2.18)	-0.25	(1.76)
Incumbent Status(INCUMBENT)	(-0.16)	-0.03	(0.08)	(-0.23)	-0.05	(0.11)
Member of Democratic Party(DEMOCRAT)	(0.03)	0.45	(0.80)	(-0.28)	0.06	(0.44)
Percent Agricultural PAC Money(AGPAC)	(0.13)	1.83	(2.94)	(0.05)	1.11	(2.41)
Urban Population %(URBAN)	(-2.39)	-1.64	(-0.11)	(-1.33)	-0.78	(-0.05)
Win Last Election %(WINLAST)	(0.03)	0.47	(0.93)	(-0.31)	0.11	(0.58)
Member Agricultural Committee(AGCOM)	(0.01)	0.15	(0.32)	(-0.06)	0.14	(0.42)
Market Value of Production(MVP)	(-17.23)	-8.98	(-0.55)	(-8.88)	-2.18	(2.85)
Government Payments(GP)	(-6.58)	-0.49	(5.25)	(-6.02)	0.33	(6.69)
ADA Score(LQ2001)	(-0.80)	-0.40	(-0.02)	(-0.36)	0.07	(0.52)
Constant	(0.09)	1.32	(2.04)	(0.03)	0.59	(1.17)

Note: Estimates based on a burn-in sample size of S = 100,000 and a Gibbs sample size of G = 100,000. Ninety-five percent highest posterior density limits are reported in parentheses.

Figures

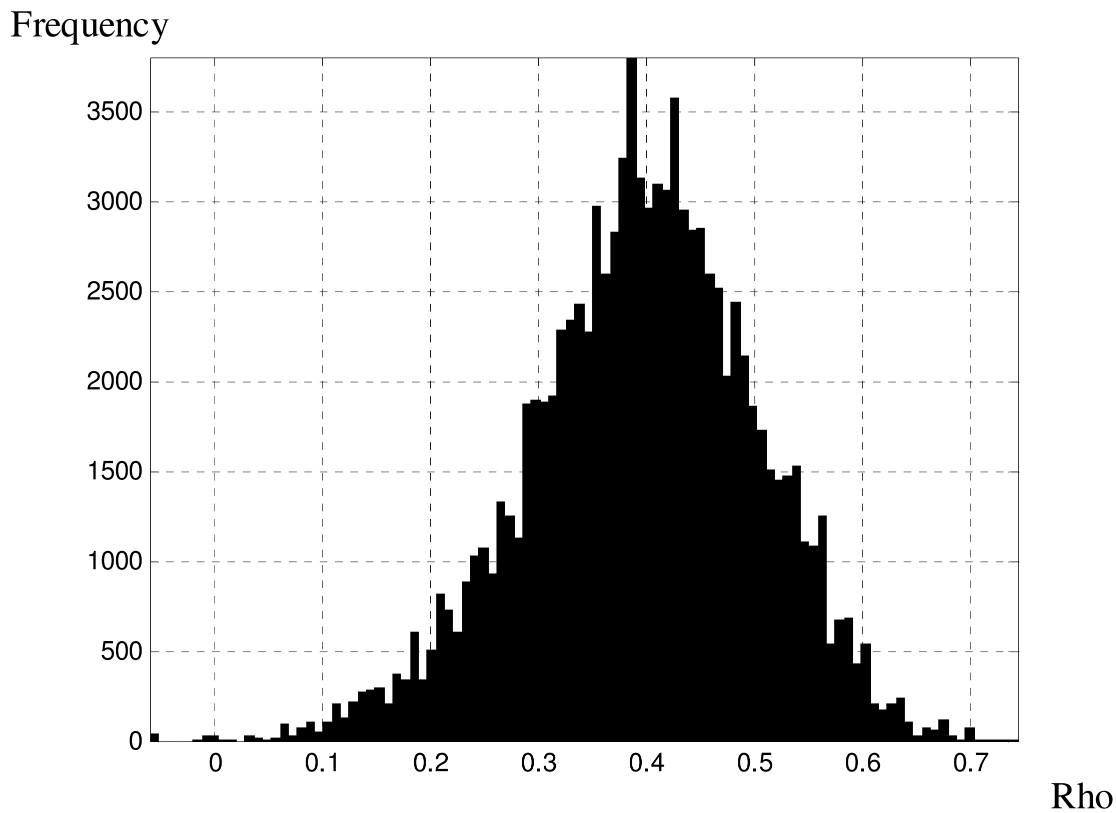

Figure 1. Posterior probability density function for the spatial correlation coefficient. Estimates are based on a burn-in sample size of S = 100,000 and a Gibbs sample size of G = 100,000.

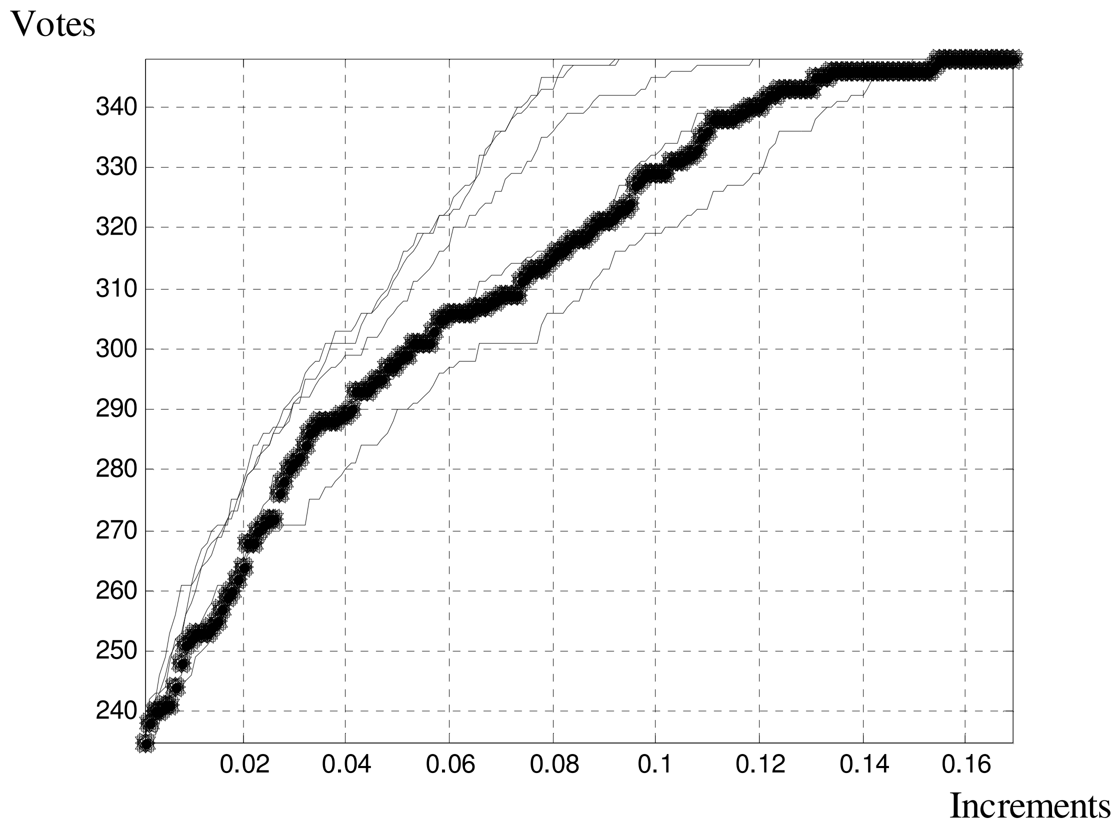

Figure 2. Impact on House votes of incremental increases in PAC contributions. The dark shaded entries denote predictions derived under the preferred model specification($\equiv \mathbf{W}^{(2,1)}$) and the remaining neighbourhood designations, depicted attaining the maximum vote capacity in order are, respectively as follows: $\mathbf{W}^{(2,5)}$; $\mathbf{W}^{(2,4)}$; $\mathbf{W}^{(2,3)}$; $\mathbf{W}^{(2,2)}$; 'magenta' $\equiv \mathbf{W}^{(2,0)}$. Estimates are based on a burn-in sample size of S = 100,000 and a Gibbs sample size of G = 100,000.