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Does Spatial Dependence Affect the Intention to Make Land Available for Bioenergy Crops?

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Abstract

We find spatial dependence in landowners' stated intentions to make land available for bioenergy crops. Our data are generated from a contingent valuation survey of 599 owners of marginal land in southern Michigan. Employing a Bayesian framework and using these spatially explicit data, we estimate and compare non-spatial probit and spatial Durbin probit models to examine the presence of spatial dependence in land rental intentions. Results show that intentions to rent land for bioenergy crop production are spatially dependent. This spatial dependence arises both from the land supply intentions of nearby landowners and from spatial spillover effects of landowner characteristics and attitudes towards environmental amenities and the disamenities of land rental. We show that ignoring spatial dependence in the intentions of neighbouring landowners to participate in land rental markets for bioenergy feedstocks can lead to distortions that underestimate total effects. Our finding implies that studies of land use and crop supply should test for spatial interactions in order to make accurate inferences.

Keywords: *Bayesian modeling*; *bioenergy crops*; *contingent valuation*; *landowners' intentions*; *spatial dependence*; *spatial probit model*.

JEL classifications: *Q15, C11*.

1. Introduction

Predicting the potential supply of land for biomass production in the United States has become the subject of intensive research since the passage of the Energy Independence and Security Act of 2007. A substantial number of authors have addressed the question of the determining factors that drive biomass supply decisions (Jensen *et al*.,

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2007; Paulrud and Laitila, 2010; Cope *et al*., 2011; Joshi and Mehmood, 2011; Tyndall *et al*., 2011; Altman and Sanders, 2012; Qualls *et al*., 2012; Villamil *et al*., 2012; Aguilar *et al*., 2014; Bergtold *et al*., 2014; Skevas *et al*., 2014, 2016; Altman *et al*., 2015; Mooney *et al*., 2015; Cai *et al*., 2016; Fewell *et al*., 2016). Despite providing valuable insight into factors affecting the supply of land for bioenergy crops, these studies ignore spatial dependence, despite its potential influence on land supply decisions.

Spatial dependence is defined as the likelihood that nearby units are more likely to be related than more distant ones, a statement often attributed to Waldo Tobler and known as the 'First Law of Geography' (Tobler, 1970). As a consequence nearby decision-making units may exhibit interdependent decision-making processes that affect their resource allocation behaviour and economic performance. These interdependencies may be the result of strategic interactions, indirect effects of exogenous factors (i.e. not under decision-makers' control) on decision-makers' choices, or spatial correlations in the environment in which decision-makers operate (Storm *et al*., 2014). Strategic interaction refers to instances where two or more individuals co-ordinate their actions for the purpose of achieving a better payoff for all group members. One way that strategic interaction could lead to spatial dependences would be if landowners choose to cluster crops for mutual benefit, as traditional Peruvian farmers do to protect against harvest loss and theft (Swinton, 2002). Skevas *et al*. (2010) found that Portuguese genetically modified (GM) maize farmers were able to reduce coexistence compliance costs through crop clustering. Spatial dependence may also arise due to indirect effects of factors that are not under the control of decision-makers such as geographic or weather conditions that favour or disfavour certain types of farming. The environment in which an individual operates, and more specifically the social group, can affect own behaviour through knowledge spillovers (Manski, 1993), which may also apply to underlying perceptions and attitudes. For instance, landowners learn about new innovations from the experience of their peers (Foster and Rosenzweig, 1995; Conley and Udry, 2010) such as neighbouring landowners, and can, for example, reduce transaction costs (e.g. information costs of making contracts), raise awareness of environmental issues, and change crop patterns and production practices. A more subtle form of correlation in the decision environment arises when landowners, through their occupation of land in a specific locality, have implicitly expressed similar preferences (e.g. for crop productivity, natural amenities, or cultural amenities). These very plausible factors could give rise to spatial dependence affecting land use or letting decisions and, since land is a key resource affecting economic performance, the value of testing for spatial dependence is obvious.

Attempts to account for spatial dependence in empirical models of decision-making in the agricultural sector can be categorised in two major strands. The first strand examines the influence of spatial dependence on technology adoption. The first study to assess neighbourhood influence on technology adoption was Case (1992) who modeled sickle adoption in Indonesia. In subsequent work, Holloway *et al*. (2002) used a Bayesian spatial probit approach to model the importance of neighbourhood effects on Bangladeshi rice farmers' decisions to adopt high-yielding varieties. Swinton (2002) compared spatial regression with zonal random effects regression to control for spatial structure in testing for evidence of linkages between farm asset levels and environmental degradation. More recently, a considerable number of studies has examined spatial dependence in the adoption of organic farming both at the farm (Nyblom *et al*., 2003; Parker and Munroe, 2007; Lewis *et al*., 2011; Wollni and Andersson, 2014; Läpple and Kelley, 2015) and regional levels (Schmidtner *et al.*, 2012; Bjørkhaug and Blekesaune, 2013).

The second strand of research assesses the importance of spatial dependence in agricultural markets. Graubner *et al.* (2011a,b) examined the effect of spatial competition on the pricing behaviour of processors. By employing a Bayesian spatial probit model, Holloway *et al.* (2007) investigated the existence of spatial dependence effects in the decision of Filipino smallholders to participate in markets, and estimated the magnitude of the spatial zone within which correlation of decision making occurs. For the land market, Benirschka and Binkley (1994) and Gellrich and Zimmermann (2007) considered spatial correlation in explaining land prices and abandonment, respectively. Unlike Benirschka and Binkley (1994) and Gellrich and Zimmermann (2007) that accounted for spatial correlations at the regional level, Storm *et al.* (2014) analysed spatial farm-level dependence. More specifically, these authors used spatially lagged explanatory variable (SLX) and spatial Durbin error probit models (SDEM) to assess the importance of spatial dependences between neighbouring farms for the effect of direct payments on farm survival. All these studies highlight the importance of spatial dependence on technology adoption, market participation or farm survival, implying that decision making in the agricultural sector should not be based on the assumption of independent farm behaviour.

In the context of bioenergy production, spatial dependence is important for several reasons. First, recent studies about bioenergy supply have recommended that energy crops be targeted towards marginal lands (Cai *et al.*, 2010; Gelfand *et al.*, 2013). This is because bioenergy production on marginal lands has the potential to mitigate competition for cropland and associated risk of food price rises (Campbell *et al.*, 2008; Carroll and Somerville, 2009; Swinton *et al.*, 2011). Marginal lands for bioenergy production are scarce and tend to be spatially associated with land that has impediments to productive crop farming, which may well give rise to spatial clustering of biomass production (Mooney *et al.*, 2015). Second, because dedicated bioenergy crops are not currently produced commercially on a large scale in the United States, landowners are generally unfamiliar with their management and are potentially inclined to seek technical information from neighbouring early adopters. Third, existing values, social norms and social networks can either inhibit or assist adoption. For instance, some landowners may value their land for amenities such as recreation opportunities (Mooney *et al.*, 2015; Skevas *et al.*, 2016), and incur disutility (e.g. from noise disturbance or smell) when neighbouring landowners convert their land to agricultural production. This in turn, may negatively influence neighbouring landowners to adopt bioenergy crops. In addition, since bioenergy production has some public good attributes, there may also be some element of free-riding in decisions to make land available for bioenergy or not.

Against this background, the objective of this study is to empirically analyse whether spatial dependence among landowners affects their willingness to make land available for bioenergy production. We apply Bayesian non-spatial and spatial Durbin probit models to stated preference data from a sample of owners of marginal land in southern Michigan, which seek to identify landowners' intentions to make land available for bioenergy crops. We contribute to the literature by being the first to assess the role of neighbour dependence on landowner willingness to make land available for bioenergy crops. Section 2 describes the conceptual model. The data and empirical framework are discussed in section 3. Section 4 presents the empirical results from the analysis. Section 5 concludes.

2. Conceptual Framework

This section provides the conceptual basis for the empirical specification (in section 3.2). The focus is on landowners' willingness to rent out land for bioenergy production. Following Swinton *et al.* (2017) and Wollni and Andersson (2014), with some minor adjustments to fit the context of our study, a landowner is assumed to make land supply decisions by maximising the following utility function:

$$\max_{A_c^l} U\left(cn\left(\pi^l\left(p_c^l, A_c^l\right) + NLI\right), TC\left(IN\left(A_c^l\right)\right), S\right) \tag{1}$$

$$s.t. \sum_c A_c^l \leq \bar{A}^l \tag{2}$$

where U is utility, cn is consumption, $\pi^l(p_c^l, A_c^l)$ is profit generated by renting land type l with A_c^l acres in crop c at rental rate p_c^l, NLI is non-land income, TC is the transaction cost of a potential land use change (e.g. from existing uses to bioenergy crops), IN is activity specific information availability, S is deviation from the social norm, and $\bar{A}^l$ is the total area available of land type l. The optimal solution to the maximisation problem is given by the bioenergy land supply equation:

$$A_c^l = A\left(p_c^l, TC\left(IN\left(A_c^l\right)\right), S|\bar{A}^l, NLI, Z\left(Att^l, LO, LM^l, LU^l, DC\right)\right) \tag{3}$$

where Z is a set of heterogeneous landowner attitudes (Att) (i.e. views on bioenergy and the environment, concerns about environmental amenities and rental disamenities,) and characteristics (i.e. land types owned (LO), land management practices (LM), land uses (LU) and demographic characteristics (DC)).

If spatial dependence affects land supply decisions (A_c^l), a landowner's i utility (U_i) received from land supply choices (A_c^l) will be correlated with the neighbour's utility j (U_j) (with $i \neq j$), underpinning the importance to control and test for spatial dependence. Spatially structured land supply decisions may arise from two distinct classes of factors that have a spatial structure. One, strategic interaction, may take the form of direct communication, resulting in information spillovers IN that impact transaction costs TC, such as the fixed costs of learning about a new technology (e.g. learning about production practices related to bioenergy crops, potential environmental risks of bioenergy crops). Information spillovers may arise from: (i) neighbouring early adopters and innovators, (ii) neighbouring economically successful and profit oriented landowners and, (iii) neighbouring well-informed landowners. A second class of factors that potentially have spatial structure are similar preferences and tastes among landowners who bought land in the same area. This could lead to correlated behaviour – even in the absence of direct communication between neighbouring landowners. For instance, people who like to hike or hunt may be more likely to buy wooded property or members of a religious community may elect to live near one another. Both instances may lead landowners to exhibit spatially structured land letting decisions that arise from underlying correlation in their attitudes and preferences. Although this study does not have the ability to determine the drivers of spatial dependence, it provides empirical evidence on the existence or lack of spatial structure.

Based on the above discussion, the arguments in equation (3) can be used to test the existence or lack of spatial structure in land supply decisions for bioenergy production. Specifically the following hypotheses are proposed:

H1: There is no spatial structure in landowners' willingness to supply land for bioenergy crops (A_c^l). But if landowners tend to cluster with others who have correlated tastes or preferences, we expect land supply decisions to be spatially correlated.

H2: Decisions to supply land for bioenergy production are not spatially structured in terms of rental contract terms (e.g. rental rate p_c^l). But if landowners who live in areas with lots of cropland are more likely to be familiar and base their rental decisions on crop rental rates and associated types of contract lengths, while landowners who live where land is used more for recreation or timber are more likely to anchor their land rental decisions around rental contract terms that prevail for those land uses, we expect land supply decisions to be spatially correlated in terms of rental contract terms.

H3: Decisions to supply land for bioenergy production are not spatially structured in terms of land management practices (LM). But if a landowner owns land in an area where landowners use their land for similar purposes (e.g. farming) and are accustomed to management practices associated with these purposes (e.g. renting land for farming purposes), we expect land supply decisions to be spatially correlated in terms of land management practices.

H4: Decisions to supply land for bioenergy production are not spatially structured in terms of types of land landowners currently own (LO). But if landowners with similar underlying preferences tend to cluster and to express those preferences in their choices of types of land to purchase, we expect land supply decisions to be spatially correlated in terms of current land types owned.

H5: Decisions to supply land for bioenergy production are not spatially structured in terms of current land uses (LU) (e.g. hunting). But if landowners cluster in areas based on their land use preferences (e.g. farming, recreation), we expect land supply decisions to be spatially correlated in terms of current land uses.

H6: Decisions to supply land for bioenergy production are not spatially structured in terms of established local social norms (S) or attitudes towards bioenergy production (Att) (Läpple and Kelley, 2013). But if a landowner believes that the neighbours appreciate or disapprove of her land use choices, we expect land supply decisions to be spatially correlated in terms of social norms or attitudes towards bioenergy.

H7: Decisions to supply land for bioenergy production are not spatially structured in terms of landowner demographic characteristics (DC) (e.g. education). But if landowners with common characteristics tend to cluster geographically, we expect land supply decisions to be spatially correlated in terms of landowners' characteristics.

3. Data and Empirical Methods

3.1. Data

We make use of a dataset described in detail in Skevas *et al*. (2016), and therefore only a brief description of the data is presented here. We use this primary data from a survey of 599 owners of non-crop marginal land in southern Michigan. The dataset includes information on willingness to rent land for production of bioenergy crops, current land use patterns, land management practices, environmental attitudes and concerns related to bioenergy production, and socioeconomic variables. The willingness to supply questions included, for given rental rates (US\$ 50, US\$ 100, US \$ 200, or US\$ 300) and contract length (i.e. 5 and 10 years), dichotomous choice questions on willingness to rent three specific land types (i.e. cropland, pasture, farmable non-crop land) for four bioenergy crops (i.e. corn, switchgrass, mixed prairie and hybrid poplar). These variables serve as our dependent variables of interest (i.e. y) in our empirical models. Real rental rates in Michigan (Wittenberg and Harsh, 2011) were used to assign values to the rental rate variable. Cropland rental rates in Michigan vary based upon crop and crop management practices (i.e. tillage, irrigation), with US\$ 84 and US\$ 111 per acre being the average rate for tilled and non-tilled cropland in Southern Lower Peninsula, respectively. The low rate used in this study (i.e. US\$ 50 per acre), corresponds to land that is economically marginal or has low agricultural value. The upper limit was set to US\$ 300, three times the current typical rental rate per acre of US\$ 100. The land use and management variables included information on whether landowners currently rented any of their land, and whether they used it for non-agricultural purposes (e.g. recreation, scenery, fishing, hunting). The attitudinal variables were derived by applying factor analysis on a set of 22 five-point Likert scale statements associated with bioenergy and the environment, concerns on renting land for bioenergy crops, and general views about the land rental process. This process resulted in the following attitudinal variables: 'renewable energy supporter', 'environmental critic', 'concerns with renting land', and 'concerns with agricultural production'. Finally, the socioeconomic variables included land area owned, whether the landowner is a farmer, landowner's age, gender, educational level and income level. Table 1 presents a summary statistics of the data used.

The stated preference question about willingness to make land of a specific type available for growing a specified bioenergy crop was framed as a land rental decision at a stated rental rate per acre. The rationale for framing the question as a land rental decision rather than as a decision for the owner to grow bioenergy crops was to avoid scenario rejection by respondents who lacked the means to grow bioenergy crops themselves. In fact, most rural landowners in southern Michigan do not farm their land and the practice of renting land out does not differ significantly between the sampled landowners who farm (35% rent out) and those who do not (29% rent out).

3.2. Empirical framework

Since the land supply decision is a binary-choice variable, we employ a spatial probit model (e.g. LeSage and Pace, 2009; Elhorst, 2014; Läpple and Kelley, 2015) to explain landowner willingness to make land available for bioenergy crops. The latent variable y^* underlying the probit model determines the outcome of the observed willingness ($y = 1$) or refusal decision ($y = 0$) to make land available for bioenergy crops:

$$y = \begin{cases} 1 \text{ if } y^* > 0 \\ 0 \text{ if } y^* \leq 0 \end{cases} \tag{4}$$

where y denotes an $N \times 1$ vector consisting of one observation on the dependent variable for each unit in the sample ($i = 1, \ldots, N$). y^* is assumed to be a linear function of the landowner's characteristics X and the neighbours' characteristics WX where W is an $N \times N$ spatial weighting matrix defined below. We further assume exogeneity of the covariates in X. To assess spatial dependence among landowners, a spatial Durbin (SD) model is considered. LeSage and Pace (2009) argue that the SD model is

Table 1
Summary statistics of data

Variable	Unit	Mean
Current land management		
Currently rents land	Percent	33
Current land owned		
Total cropland	Acres	87
Total pasture	Acres	13
Total farmable non cropland	Acres	17
Total land in Conservation Reserve Program (CRP)	Acres	5
Current land uses		
Landowner used land for scenery	Percent	62
Landowner used land for physical activities	Percent	53
Landowner used land for hunting or fishing	Percent	69
Landowner used land for grazing livestock	Percent	19
Landowner used land for commercial crop income	Percent	26
Landowner used land for conservation income (CRP payments)	Percent	28
Demographic information		
Age	Years	62
Male	Percent	79
Farmer	Percent	41
Pre-tax income		
Less than US$ 25.000	Percent	10
US$ 25.000–49.999	Percent	25
US$ 50.000–99.999	Percent	43
US$ 100.000–149.999	Percent	11
US$ 150.000–199.999	Percent	4
US$ 200.000 and above	Percent	7
Education		
Less than 12 years	Percent	5
Completed high school or GED	Percent	28
Technical training beyond high school	Percent	14
Some college (including AA, AS degrees)	Percent	21
Four-year college degree	Percent	16
Some graduate work	Percent	4
Graduate degree	Percent	12

***Source*:** Skevas *et al*. (2016).

preferred when there is uncertainty over the existence of spatial dependence in the dependent variable (i.e. the outcomes) versus the error. In the SD model, which may result from a simple rearrangement of the spatial error (SE) model, spatial correlation in the error term is controlled by the spatial lags of the dependent and explanatory variables (Gibbons and Overman, 2012). The SD model takes the form:

$$y^* = \rho W y^* + X\beta + WX\theta + \in \tag{5}$$

When ρ, $\theta = 0$ the SD model reduces to a non-spatial probit model.

The associated data-generating process of (5) can be written as follows:

$$y^* = (I_N - \rho W)^{-1}(X\beta + WX\theta + \in) \tag{6}$$

where X denotes an $N \times K$ matrix of exogenous explanatory variables, β and θ are $K \times 1$ vectors of unknown parameters to be estimated, WX denotes the exogenous interaction effects among the independent variables, I_N is an n-dimensional identity matrix, and $e = (e_1, \ldots, \epsilon_N)$ is an $N \times 1$ vector of disturbance terms that are assumed to be independently and identically distributed $\in \sim N(0,I_N)$. In the SD model, an influence on land supply decisions is exerted by (i) the neighbours' decisions to supply land for bioenergy crops (through ρWy^*), (ii) the landowner's characteristics and attitudes towards bioenergy production (through $X\beta$), and (iii) the characteristics and attitudes of the neighbouring landowners and their land (through $WX\theta$).

We estimate the SD model using a Bayesian approach which has proven its potential in effectively estimating spatial probit models (LeSage and Pace, 2009). Frequentist methods require the use of numerical optimisation techniques as the first-order terms of the log-likelihood function are not analytic. In contrast, Bayesian methods are based on a simpler computational framework, as the powerful tool of Markov Chain Monte Carlo (MCMC) simulation replaces numerical integration by simulating from the posterior distribution. The use of a Bayesian framework allows for a more intuitive interpretation of the results where inferences are valid even in small samples, while it allows for incorporation of prior beliefs in a transparent way. The Bayesian approach proceeds as follows: First, we collect all parameters to be estimated in a vector $\mu = [\rho, \beta, \theta]'$. Then, the likelihood function of the model $p(y|\mu)$ needs to be defined while prior distributions $p(\mu)$ need to be specified for all structural parameters. Finally, via Bayes' rule, the posterior density of the model's parameters can be written as:

$$p(\mu|y) \propto p(y|\mu)p(\mu). \tag{7}$$

Since the dependent variable y is a binary variable, a Bernoulli distribution is used to specify the likelihood function $p(y|\mu)$. The parameterisation of priors $p(\mu)$ is presented in Table A1 in the Appendix. We treat the binary observations in y as indicators of the latent (unobserved) variable y^* which is replaced by the estimated parameters ρ, β, θ by sampling from the conditional posterior distributions using MCMC techniques. This allows us to conclude that $p(\rho, \beta, \theta|y^*) = p(\rho, \beta, \theta|y^*, y)$. The intuition here is that the conditional posterior distribution for ρ, β, θ is equivalent to a model involving a continuous dependent variable rather than a discrete one (LeSage and Pace, 2009).

Three effect estimates are derived from estimating the SD model: (i) direct, (ii) indirect, and (iii) total effects. The direct effect is interpreted as the impact of changing a particular explanatory variable for a particular landowner on the dependent variable for that landowner. The indirect effect measures the impact of changing a particular element of an explanatory variable on the dependent variable of all other landowners (Elhorst, 2014). A total effect can also be computed that indicates how a change in an explanatory variable impacts the probability of all landowners in the sample to supply land for bioenergy crops. Some of the advantages of the SD model are that it allows the direct and indirect effects to differ across different sample units, and permits the ratio between direct and indirect effects to differ across explanatory variables (Elhorst, 2014).

The direct and indirect effects of the K explanatory variables in the SD model are computed by taking the partial derivatives of the expected value of y^* with respect to each of the K explanatory variables X for all units in the sample. This results in the following matrix: $(I_N - \rho \mathrm{W})^{-1}(\beta_k + W\theta_k)$. The average of the diagonal elements of this matrix is the mean direct effect, the average row-sum of the non-diagonal elements is the mean indirect effect, while, the sum of the mean direct and the mean indirect effect yields the mean total effect (Elhorst, 2014). A more detailed explanation on how to derive direct and indirect effects of spatial econometric models, including the SD model, can be found in (Elhorst, 2014).

On the basis of the information presented above and the variables available in the dataset, we can form the empirical version of the hypotheses presented in section 2:

H1: Landowners' land supply decisions are not affected by their neighbours' willingness to supply land for energy crops ($\rho = 0$, *otherwise* $\rho \neq 0$)*).*

H2: Neighbourhood rental contract terms do not affect land supply decisions for bioenergy production ($\theta_K = 0$, *otherwise* $\theta_K \neq 0$, *where* $K =$ *rental rate, contract length (CL)).*

H3: Neighbourhood land management practices do not affect land supply decisions for bioenergy production ($\theta_K = 0$, *otherwise* $\theta_K \neq 0$, *where* $K =$ *rents land).*

H4: Neighbourhood land type ownership does not affect land supply decisions for bioenergy production ($\theta_K = 0$, *otherwise* $\theta_K \neq 0$, *where* $K =$ *cropland, pasture, farmable non-crop land (FNC), land in Conservation Reserve Program (CRP)).*

H5: Neighbourhood current land uses do not affect land supply decisions for bioenergy production ($\theta_K = 0$, *otherwise* $\theta_K \neq 0$, *where* $K =$ *non-land based uses (NLB), hunting related uses (HRU), grazing livestock (GL), commercial income (CMI), conservation income (CNI)).*

H6: Neighbourhood social norms or attitudes towards bioenergy production do not affect the decision to make land available for bioenergy crops ($\theta_K = 0$, *otherwise* $\theta_K \neq 0$, *where* $K =$ *renewable energy supporter (RES), environmental critic (EC), agricultural based concerns (ABC), and renting land based concerns (RLB)).*

H7: Neighbourhood demographic characteristics do not affect landowners' willingness to supply their land for bioenergy production ($\theta_K = 0$, *otherwise* $\theta_K \neq 0$, *where* $K =$ *age, gender, farmer, income, education).*

3.3. Spatial weighting matrix

In order to estimate the SD models we need to specify a spatial weighting matrix W, which approximates the neighbouring relations between landowners. When using micro data, investigators often do not know the pattern of spatial correlation within the sample (Bell and Dalton, 2007). For instance, in our study, landowners' parcels are scattered over the landscape, and most respondents do not own parcels that share borders with parcels of other respondents. Hence, investigators often use weights as a function of distance between units. Knowledge of the study population and economic theory can be used to guide the specification of the weighting matrix. We apply an inverse distance matrix W, whose elements w_{ij} are $1/d_{ij}$, where d_{ij} is the Euclidean distance between landowner i and j, if two individuals own land within a certain distance, and 0 otherwise. An inverse distance matrix is preferred since it places a higher weight on closer than more distant neighbours. This approach assumes that beyond a certain distance spatial effects no longer affect the willingness of landowners to make land available for bioenergy production. The minimum distance cut-off was set to 20 km. To address concerns that results may be sensitive to the distance cut-off (Bell and Dalton, 2007), we estimate models with 30, 40 and 50 km distance cut-offs. We row standardise W so that the sum of the row elements equals 1. Since the row elements of W capture the impact on a particular unit by all other units, the weighting operation can be interpreted as an averaging of neighbouring values.

4. Results

First, we present evidence of spatial structure. Then we present the non-spatial regression results, and compare them with results from the SD models.

The SD models show strong evidence of spatial autoregressive structure (as measured by the parameter ρ) across specifications across weight matrices at all four distance cut-offs. Since there is no significant difference in the economic interpretation of ρ and the direct and indirect effects across the different weighting matrix specifications, we present the results of the estimates of the model with a 20 km distance cut-off.[2] Table 2 shows the spatial autoregressive parameter estimates and associated 95% credible intervals. All the estimated parameters are positive and significant (i.e. the credible intervals do not span zero), implying that the supply of all land types for all bioenergy crops by one landowner positively influences the supply of neighbouring landowners. We thus reject null hypothesis H1 of lack of spatial correlation in land supply decisions for bioenergy production.

Table 2

Spatial autoregressive parameter estimates for all SD models

Model	ρ - spatial autoregressive parameter	95% credible intervals	
Corn cropland	0.24	0.03	0.58
Corn pasture	0.25	0.04	0.59
Corn other	0.26	0.04	0.61
Switchgrass cropland	0.23	0.03	0.57
Switchgrass pasture	0.23	0.03	0.56
Switchgrass other	0.30	0.05	0.66
Prairie cropland	0.21	0.03	0.53
Prairie pasture	0.29	0.05	0.65
Prairie other	0.23	0.03	0.54
Poplar cropland	0.23	0.03	0.56
Poplar pasture	0.24	0.03	0.58
Poplar other	0.18	0.02	0.47

[2]The results of the estimated SD models with 30, 40, and 50 km distance cut-offs are available from the authors upon request.

The direct, indirect, and total effects of the coefficients and their corresponding 95% credible intervals are presented in the right panels of Tables B2–B13 in the online Appendix.[3]

To identify the relevance of spatial analysis of energy biomass supply, we begin with the non-spatial probit results. A summary of all significant variables in the non-spatial probit models is given in the left panel of Table 3 (with full results available in the left panels of Tables B2–B13 in the online Appendix). The rental rate offered consistently exhibited a significantly positive effect across all models. Whether the landowner rents land also had a significant and positive effect on land supply decisions across most non-spatial probit models. Other drivers of the land rental decision are current land owned (i.e. cropland, CRP and other land), current land uses (i.e. non-land based uses, hunting related uses, and use of land for commercial and conservation income), land rental concerns, whether the landowner is a farmer, and education. Landowners who use their land for recreation are more likely to let land for bioenergy perennials. Using land for hunting increases the probability of letting land for corn since it can provide forage for game species. Using land for commercial income increases the probability of letting land for bioenergy perennials. Landowners who use their land for conservation income are less willing to let land not only for corn but also for switchgrass and prairie. Concerns about land rental tended to discourage landowners from making land available for bioenergy crops. Landowners who farm their land are less willing to make cropland available for hybrid poplar trees and pasture land for switchgrass and mixed prairie. Finally, more educated landowners are more likely to participate in renting land for bioenergy perennials.

Moving to discussion of the coefficient estimates in the SD model, a summary of the statistically significant covariates in each one is given in the right panel of Table 3. The direct effects reflect how changes in explanatory variables affect the own decision to supply land for bioenergy crops, while the indirect effects show the impact on other landowners' choices. The cumulative effect of these two impacts is the total effect which reflects the effect on all landowners in the sample.

An examination of the significant covariates of the non-spatial probit and SD model by crop and land type (Table 3) reveals that, in most cases, the variables that are significant in the non-spatial model retain their significance in the SD models. However, the relative importance of the model variables (Table 3, left panel) differs considerably when including spatial lags of the dependent and explanatory variables. More specifically, when comparing the coefficient estimates of the statistically significant non-spatial model variables with their corresponding direct effects in the SD models, we find that, in the latter case, regression estimates in the SD models have on average changed in absolute value by 21%. Moreover, the significant spatial autoregressive parameter estimates (Table 2) and indirect effects of the explanatory variables (Table 3, right panel) indicate the existence of spatial dependence in land supply decisions.

Similar to the non-spatial probit models, the main drivers of the land supply decision in the models that account for spatial dependence in land rental choices (i.e. SD models) are the rental rate offered, whether the landowner currently lets land, current

[3]Robustness checks with respect to the inclusion of squared terms of landowner's characteristics X have resulted in insignificant coefficient estimates (these results are available from the authors upon request). Hence, the linearity assumption remains valid.

Table 3

Summary table of significant variables in the non-spatial probit and SD models

Model	Non-spatial probit	SD model Direct effect	 Indirect effect	 Total effect
Corn on cropland	Rental rate (+) Rents land (+) NLB (+) CNI (−) RLB (−)	Rental rate (+) Rents land (+) NLB (+) CNI (−) RLB (−)	Rental rate (+) Rents land (+) NLB (+) CNI (−) RLB (−)	Rental rate (+) Rents land (+) NLB (+) CNI (−) RLB (−)
Corn on pasture land	Rental rate (+) Rents land (+) HRU (+) CNI (−) Male (+)	Rental rate (+) Rents land (+) HRU (+) Male (+)	Rental rate (+)	Rental rate (+) Rents land (+) HRU (+)
Corn on other land	Rental rate (+) NLB (−) HRU (+) CNI (−) EC (+)	Rental rate (+) CL (+) HRU (+) CNI (−) EC (+) ABC (+)	Rental rate (+) HRU (+) CNI (−)	Rental rate (+) CL (+) HRU (+) CNI (−) EC (+)
Switchgrass on cropland	Rental rate (+) CL (−) Rents land (+) NLB (+) Education (+)	Rental rate (+) Rents land (+) CL (−) NLB (+) GL (−) EC (−) RLB (−) Income (−)	Rental rate (+) Rents land (+) NLB (+) GL (−) Education (+)	Rental rate (+) Rents land (+) CL (−) NLB (+) GL (−) EC (−)
Switchgrass on pasture land	Rental rate (+) Rents land (+)	Rental rate (+)	Rental rate (+)	Rental rate (+)
Switchgrass on other land	Rental rate (+) FNC land (+) CMI (+) CNI (−) RLB (−)	Rental rate (+) FNC land (+) CNI (−) RLB (−) Education (+)	Rental rate (+) CNI (−)	Rental rate (+) FNC land (+) CNI (−)
Prairie on cropland	Rental rate (+) CL (−) Rents land (+) CRP Land (+) NLB (+) Education (+)	Rental rate (+) Rents land (+) CRP land (+) NLB (+) Education (+)	Rents land (+) CRP Land (+) NLB (+) Education (+)	Rental rate (+) Rents land (+) CRP land (+) NLB (+) Education (+)
Prairie on pasture land	Rental rate (+) Rents land (+) Farmer (−) Education (+)	Rental rate (+) Rents land (+) Farmer (−) Education (+)	Rental rate (+) Farmer (−) Education (+)	Rental rate (+) Rents land (+) Farmer (−) Education (+)
Prairie on other land	Rental rate (+) CNI (−)	Rental rate (+)	Rental rate (+)	Rental rate (+)

Table 3
(*Continued*)

Model	Non-spatial probit	SD model Direct effect	SD model Indirect effect	SD model Total effect
Poplar on cropland	Rental rate (+) Rents land (+) Cropland (+) CMI (+) CNI (−) RLB (−) Farmer (−)	Rental rate (+) Cropland (+) NLB (+) CMI (+) RLB (−) Farmer (−)	Rental rate (+) CMI (+) RLB (−) Farmer (−)	Rental rate (+) NLB (+) CMI (+) RLB (−) Farmer (−)
Poplar on pasture land	Rental rate (+) Farmer (−)	Rental rate (+) Farmer (−)	Rental rate (+) Farmer (−)	Rental rate (+) Farmer (−)
Poplar on other land	Rental rate (+) FNC land (+) CMI (+) RLB (−)	Rental rate (+) FNC land (+) CMI (+) Farmer (−)	Rental rate (+) FNC land (+) CMI (+)	Rental rate (+) FNC land (+) CMI (+)

Note: + or − in parentheses shows the direction of the relationship between an explanatory variable and the land supply decision. CL, FNC, CRP, NLB, HRU, CMI, CNI, EC, ABC, RLB stand for contract length, farmable non-crop, Conservation Reserve Program, non-land based uses, hunting related uses, commercial income, conservation income, environmental critic, agricultural based concerns, and renting land based concerns, respectively.

land owned (i.e. the amount of CRP, and farmable non-crop land a landowner owns), current land uses (i.e. non-land based uses, hunting related uses, and use of land for commercial and conservation income), land rental concerns, whether the landowner is a farmer, and education. The SD model results that follow are organised by our seven hypotheses.

The rental rate offered has a significantly increased direct probability of letting land for bioenergy crops in all SD models (i.e. 16–57% increase in probability). The indirect effects of the rental rate variable are significant in 11 out of the 12 SD models, with an effect that ranges between 3% and 16% increase in probability. The total effect of the rental rate variable shows an increase in probability of land rental that ranges between 19% and 73%. The significant indirect effects of the rental rate variable lead us to reject the null hypothesis H2 of no presence of spatial structure in terms of rental contract terms.

Whether the landowner currently lets land increases the direct probability of letting land for most bioenergy crops (except hybrid poplar), but depends on the land type. Landowners who currently let land are willing to let cropland for corn, switchgrass and mixed prairie, and pasture land for corn and mixed prairie production. The indirect effect of this variable is positive and significant for corn (i.e. 0.27), switchgrass (i.e. 0.10) and mixed prairie (i.e. 0.07) on cropland. This implies that spatial spill-overs of prior land rental increase the probability of cropland supply for corn, switchgrass and mixed prairie on neighbouring ownerships by 27%, 10% and 7%, respectively. This result implies rejection of the null hypothesis H3 of absence of spatial structure in terms of land management practices. The total effect of the land rental variable shows a 113%, 31%, 43%, and 40%, respectively for an increase in the collective probability of land supply for corn on cropland, corn on pasture land, switchgrass on cropland, and prairie on cropland.

In terms of the type of land landowners currently own, owning more land in the Conservation Reserve Program (CRP) and farmable non-crop land increases the collective probability of supplying land for bioenergy crops based on both own and nearby properties. This is true for the supply of farmable non-crop land for switchgrass and hybrid poplar, and cropland for mixed prairie. However, these effects are economically insignificant (i.e. <1% change in the land supply probability), so there is no basis for rejecting hypothesis H4 of no spatial structure in terms of types of land landowners currently own.

In terms of current land uses, the variable 'non-land based uses' which captures use of lands for recreation, physical activities or scenery, exhibits a significant positive direct effect only for the supply of bioenergy crops on one land type – cropland. The indirect effect of this variable is small but positive in the case of cropland supply for all bioenergy crops (except hybrid poplar). There are two possible explanations: (i) correlated behaviour among landowners who share underlying preferences for amenity-based land uses, and/or (ii) social interactions shaping the belief that land supply decisions could enhance neighbours' utility derived from using land for amenities. This effect ranges from a 3% increase in probability of land supply for prairie to 6% for switchgrass. Landowners who use their land for hunting are more willing to supply their pasture and farmable non-crop land for corn production. This is not surprising since corn fields can provide adequate cover and forage for deer, especially in summer and early fall (VerCauteren and Hygnstrom, 1994). The magnitude of this effect is 21% and 32% for pasture and farmable non-crop land, respectively. This also impacts the landowner's neighbours' supply decisions with a cumulative indirect effect of 8% and 11%, accumulating to a total effect of 30% and 43% for renting pasture and farmable non-crop land for corn, respectively.

Using land for commercial income increases the landowner's direct probability of renting out cropland (34%) and farmable non-crop land supply (25%) for hybrid poplar cultivation. Cultivation of commercial crops on own land also impacts on the supply of nearby landowners, with a cumulative indirect effect of 11% and 7% for letting cropland and farmable non-crop land for hybrid poplar, respectively. The combined total effect of both landowner and neighbours' choices is a 45% and 32% increase in the probability of supplying cropland and farmable non-crop land for hybrid poplar, respectively. Profit orientation is also an important factor that affects both own and neighbouring adoption decisions in Läpple and Kelley's (2015) study of organic farming adoption in Ireland.

Landowners who use their land for conservation income are less likely to rent cropland and farmable non-crop land for corn. This also negatively affects the landowners' neighbours' supply decisions (in the case of renting farmable non-crop land for corn and switchgrass, and cropland for corn) with a cumulative indirect effect that ranges between 10% and 12% reduction in the probability of supply, accumulating to a total effect of between 28% and 48% decrease in probability. The significant indirect effects of the land use variables (i.e. 'non-land based uses', 'hunting related uses', 'commercial income', 'conservation income') lead to the rejection of the null hypothesis H5 of lack of spatial structure in terms of land uses.

In terms of attitudinal variables, the concerns about renting land ('Renting land based concerns') have a significant effect on the probability of willingness to supply cropland for corn, switchgrass and hybrid poplar production, and farmable non-crop land for switchgrass. More specifically, an increase in land rental concerns decreases the landowner's direct probability of growing corn on cropland by 14%. This also impacts on neighbours' land supply decisions with a cumulative indirect effect of 5% reduction in the probability of supply, accumulating to a total of 19% probability decrease. Land rental concerns also decrease the probability of renting cropland and farmable non-crop land for switchgrass, by 11% and 7%, respectively. Concerns about renting land discourage participation of the landowner in renting cropland for hybrid poplar (direct effect of 13% reduction). The spatial spillover effect for this variable is 5% reduction in the probability of supply, while the combined total effect on all landowners is 18% decrease in probability. The significant spatial spillover effects of the land rental concerns variable provides important empirical evidence that landowners' land supply decisions are correlated with their neighbours' attitudes. This leads us to reject the null hypothesis H6 of no presence of spatial structure in terms of landowners' attitudes towards bioenergy production. The attitudinal variables 'renewable energy supporter' and 'environmental critic' had no significant indirect effect in any SD model, so there is no basis for rejecting the null hypothesis H6 of lack of spatial structure in terms of social norms (related to bioenergy production).

In terms of landowners' characteristics, income has a negative effect on the probability to supply cropland for switchgrass (i.e. a direct effect of 30% reduction in the probability of supply), implying that more wealthy landowners are less likely to supply this type of land. Being a farmer has a negative effect on the probability of pasture land supply for mixed prairie and all land types for hybrid poplar (i.e. this effect ranges from 15% to 35% reduction in probability). This also impacts on neighbours' land supply decisions (in the case of pasture land supply for mixed prairie and hybrid poplar, and cropland for hybrid poplar) with a cumulative indirect effect that ranges between 9% and 12% reduction in the probability of supply, culminating in a total effect that ranges between 31% and 45% probability decrease. Finally, more educated landowners are more likely to rent their cropland and pasture land for mixed prairie, and farmable non-crop land for switchgrass. In the case of making cropland available for the cultivation of mixed prairie, an increase in the level of education by one standard deviation increases the probability of supply of this landowner by 23%. This also impacts on neighbours' land supply decisions with a cumulative indirect effect of 8%, culminating in a total of 31% probability increase. The direct, indirect and total effects in the case of pasture land supply for mixed prairie are 27%, 12% and 39% increase in the probability, respectively. In contrast, in their study on organic farming adoption in Ireland, Läpple and Kelley (2015) did not find a significant effect of education on landowners' adoption decisions. The significant spatial spillover effects of the farmer and education variables lead us to reject null hypothesis H7 of no spatial structure in landowner characteristics.

5. Conclusions

This study used non-spatial and SD probit models under a Bayesian framework to assess the effect of spatial dependence on landowners' stated willingness to supply land for bioenergy production. The application focuses on contingent valuation data from owners of marginal land in southern Michigan and provides evidence of the importance of spatial dependence in land rental intentions.

The results of the SD models prompt two important conclusions. First, landowner land supply decisions depend jointly on their neighbours' decisions, attitudes and characteristics. Second, the findings of this study provide some empirical evidence on the channels of landowner dependences. These channels are: (i) neighbours' attitudes on the land rental process related to bioenergy production, (ii) neighbouring profit oriented and highly educated landowners, and (iii) indirect effects of renting land for bioenergy crops on neighbouring landowners' utility derived from amenities. Land rental concerns, such as concerns about the type and length of rental contracts for bioenergy production, reduce the landowner's and neighbours' probability of letting cropland for certain bioenergy crops (i.e. corn, switchgrass and hybrid poplar). This implies that neighbours' attitudes towards bioenergy production correlate with owners' land supply decisions. Similar to our findings, Läpple and Kelley (2015) also find a significant effect of neighbours' attitudes on the uptake of organic farming in Ireland. An implication of this finding for contractors seeking to expand the acreage in energy crops is that introducing more flexible contractual arrangements that minimise land visits could allay landowners' and neighbours' land rental concerns. The proximity of profit-oriented landowners is associated with a positive influence on land supply decisions for hybrid poplar. In the case of supplying farmable non-crop land for hybrid poplar, profit-focused landowners may be more aware of the suitability of unproductive land to growing hybrid poplar and the opportunity to gain income from such activity. Likewise, proximity to highly educated landowners has a positive influence on land supply decisions for mixed prairie, perhaps because they are more aware of its environmental benefits (e.g. increase in biodiversity) and eligibility for conservation payments and livestock grazing. Perceived benefits from renting land for bioenergy perennials on own and neighbours' utility derived from amenities, increase the supply of land for these crops. This suggests that diffusion of information on the suitability of bioenergy perennials for private amenity consumption will increase the supply of land for these crops. Bioenergy perennials are also suitable for conservation agriculture that could potentially provide an additional income for the household.

Taken together, these findings have important implications for policy-makers seeking to expand the supply of land for bioenergy crops. Since the decision to supply land for bioenergy crops is influenced not only at the individual level (as shown in the study by Skevas *et al.*, 2016) but also by processes that take place at the neighbourhood level, policies aiming at increasing the uptake of bioenergy crops should not assume independent landowner behaviour but account for spatial interactions among neighbouring landowners. For instance, extension programmes targeting neighbourhood networks rather than individuals may be more effective in overcoming the barriers of participation in bioenergy markets at the individual level. Participatory extension programmes can foster social learning among participants, and provide a platform where landowners who are more appreciative of the economic and environmental benefits of bioenergy crops can alleviate the concerns of those with reservations about bioenergy crops. Since this research shows that land supply decisions for bioenergy production are spatially dependent, future work should attempt to identify spatial agglomerations where landowners favour bioenergy crops and their costs of provision could be lower (Mooney *et al.*, 2015).

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table B1. List of variables with abbreviations used in Tables B2–B13 in the online Appendix.

Table B2. Model comparison of the estimation results explaining the supply of cropland for corn.

Table B3. Model comparison of the estimation results explaining the supply of pasture land for corn.

Table B4. Model comparison of the estimation results explaining the supply of other land for corn.

Table B5. Model comparison of the estimation results explaining the supply of cropland for switchgrass.

Table B6. Model comparison of the estimation results explaining the supply of pasture land for switchgrass.

Table B7. Model comparison of the estimation results explaining the supply of other land for switchgrass.

Table B8. Model comparison of the estimation results explaining the supply of cropland for mixed prairie.

Table B9. Model comparison of the estimation results explaining the supply of pasture land for mixed prairie.

Table B10. Model comparison of the estimation results explaining the supply of other land for mixed prairie.

Table B11. Model comparison of the estimation results explaining the supply of cropland for hybrid poplar.

Table B12. Model comparison of the estimation results explaining the supply of pasture land for hybrid poplar.

Table B13. Model comparison of the estimation results explaining the supply of other land for hybrid poplar.

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Appendix

Table A1. Parameterisation of priors

Parameter	Distribution	Probability density function	Hyper-priors
β	$N(b, S)$	$\frac{\lvert S\rvert^{-\frac{1}{2}}}{(2\pi)^{\frac{K}{2}}} exp\left\{-\frac{(\beta-b)' S^{-1}(\beta-b)}{2}\right\}$	$b = 0_K$, $S = 1{,}000 \times I_K$
θ	$N(d, P)$	$\frac{\lvert P\rvert^{-\frac{1}{2}}}{(2\pi)^{\frac{L}{2}}} exp\left\{-\frac{(\delta-d)' P^{-1}(\delta-d)}{2}\right\}$	$d = 0_L$, $P = 1{,}000 \times I_L$
ρ	Beta(a, b)	$\frac{\rho^{\alpha-1}(1-\rho)^{\beta-1}}{B(a,b)}$	$\alpha = 2$, $\beta = 4$