Land Use Change: A Spatial Multinomial Choice Analysis

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Abstract

Urban decentralization and dispersion trends have led to increased conversion of rural lands in many urban peripheries and exurban regions of the U.S. The growth of the exurban areas has outpaced growth in urban and suburban areas, resulting in growth pressures at the urban-rural fringe. A thorough analysis of land use change patterns and the ability to predict these changes are necessary for the effective design of regional environmental, growth, and development policies. We estimate a multinomial discrete choice model with spatial dependence using parcel-level data from Medina County, Ohio. Accounting for spatial dependence should result in improved statistical inference about land use changes. Our spatial model extends the binary choice "linearized logit" model of Klier and McMillen (2008) to a multinomial setting. A small Monte Carlo simulation indicates that this estimator performs reasonably well. Preliminary results suggest that the location of new urban development is guided by a preference over lower density areas, yet in proximity to current urban development. In addition, we find significant evidence of spatial dependence in land use decisions.

Introduction

Land-use changes that have occurred in the United States over the past few decades have given rise to a series of intricate land use and land management policy issues. Urban decentralization and dispersion trends have led to increased conversion of rural lands in many urban peripheries and exurban regions of the U.S. Growth in exurban areas has outpaced growth in urban and suburban areas, causing substantial fragmentation of the rural landscape and creating growth pressures in the urban-rural fringe. In addition, the concurrent increase in exurban population and decrease in traditional rural population have widely changed the nature of the rural environment and the composition of rural population in the area.

Land-use changes occurring in the urban-rural fringe and beyond warrant examination for the following reasons. First, these areas are increasingly hosting a high degree of land-use change activities (Brown et al., 2005). Second, land development occurring at the urban-rural fringe is typically low-density and land intensive (Rusk, 1999). This form of development raises inefficiency concerns and is often referred to as “urban sprawl”. Third, direct connections exist between individual economic choices regarding land use and aggregate impacts of land-use changes (Bell and Irwin, 2002). Hence, studying individual land use decisions helps understand and explain the formation of land-use patterns. Lastly, individual landowners’ decision making is driven by private incentives. Yet, their decisions have serious environmental, social, and economic consequences that need to be addressed in public policy formulations. These decisions incur costs that are often not internalized (Burchell, 1998). Thus, inefficiencies in patterns of land use emerge. Understanding these dynamics is necessary to make a meaningful contribution to the policy debates regarding land use.

Land-use changes and the resultant spatial land-use patterns are generally described as the consequence of interactions among combinations of human factors (e.g. population, technology, economic conditions) and biophysical factors (e.g. soil, climate, topography) over a wide range of temporal and spatial dimensions. While temporal dynamics have received an extensive attention in economic analyses of land-use change, the treatment of spatial dynamics has frequently followed two approaches: it has either been ignored (e.g., McMillen, 1989), resulting in potentially inconsistent estimation and improper statistical inference, or spatially disperse data have been aggregated, resulting in artificially sharp intraregional differences or unrealistic interregional uniformity (Bockstael, 1996). This is not surprising given the complexity of spatial dependence. Spatial explicit analysis can help identify critical locations of land-use change and provide novel insights regarding the land use conversion process. Incorporating spatial dependence also contributes to the ultimate goal of developing a model that can reliably predict changes in land-use patterns and help understand them.

In this paper, we follow a spatial explicit approach to help identify the factors that drive the land use conversion process and explain the emerging land use patterns. Of particular interest is the identification of the factors responsible for the observed sprawling patterns of urban land development, defined as urban development that occurs in fragmented and dispersed patterns across the landscape (Carrión-Flores and Irwin, 2004).

The area of interest in our study is an urban-rural fringe county within the metropolitan area of Cleveland, Ohio—Medina County—due to its various patterns of new urban development occurring in the fringe. Four land uses are considered in the analysis: agricultural, residential, commercial, and industrial. The prevalent land development in this region is residential, accounting for more than 85 percent of land development in the last 30 years. The observed pattern of residential land use has become more fragmented and dispersed over time aligning with our definition of sprawl development. Unlike residential development, commercial and industrial land development has become more clustered over time suggesting the presence of agglomeration economies. These land development patterns indicate divergent development processes for different land uses. Therefore, encompassing multiple land uses provides a more comprehensive analysis of the spatial pattern of land use change. The parcel database is comprised of data from the Medina County Auditor's office records. It includes information on 1990-1996 land uses among other characteristics of each parcel, major roads, soil type, and population and income data. The parcel-level data allows addressing not only the spatial heterogeneity of the landscape (e.g. soil type) and policies (e.g. zoning), but also spatial dependence on the land use change decisions.

We borrow an economic model of land use conversion from a rich available literature, in which land use changes are modeled explicitly. The base of the economic model is an economic agent who is assumed to make an inter-temporal, profit maximizing choice regarding the conversion of a parcel of land to some available alternative use. Since only a number of factors that affect the stream of returns and the cost of conversion are observable to the analyst, the net returns are decomposed into a random unobservable portion and a systematic portion. This treatment of the net returns allows for a reformulation of the optimal land use decision and allows for probabilistic statements about the choice by the landowner. Since the data on land use is typically categorical and the choice of land use is mutually exclusive, the theoretical model leads naturally to an empirical discrete-choice framework (e.g., McMIllen, 1989). Our empirical model is analogous to other spatially-explicit land use change models estimated at the parcel-level within a discrete choice framework (e.g., Bockstael, 1996; Carrión-Flores and Irwin, 2004; Irwin, 2002; Kline and Alig, 1999; Landis and Zang, 1998).

The application of discrete-choice spatial econometric models to rich-data environments is problematic due to a number of econometric challenges such as spatial heteroskedasticity and autocorrelation, spatial heterogeneity, and selection bias. If these problems are overlooked, modeling methods will lead to inconsistent estimates and are as a result inappropriate for hypothesis testing and prediction (McMillen, 1992). However, the conventional maximum likelihood estimation procedure typically employed in estimating discrete choice models becomes cumbersome and infeasible because the likelihood function involves integrals of dimension equal to the sample size. Other proposed estimators in the literature provide consistent estimates under spatially dependent data for the binary choice case (e.g. Case, 1992; LeSage, 2000; McMillen, 1992; Pinkse and Slade, 1998). However, these estimators become infeasible as well in large data sets due to their requirement of inversion of large matrices. Another recent attempt to incorporate spatial (error) dependence in a multinomial probit context is found in Schnier and Felthoven (2009).

An important innovation of this research is the introduction of a feasible estimator for the multinomial choice model with a spatially lagged dependent variable that can be estimated with large samples. Klier and McMillen (2008) propose a linearized version of the generalized method of moments (GMM) estimator developed in Pinkse and Slade (1998) for the binary choice model. We extend their binary choice "linearized logit" model to a multinomial setting, thereby analyzing multiple land uses. The linearization avoids the $(n \times n)$ matrix inversion required in estimation, thus circumventing the computational infeasibility for large samples by reducing the estimation of the model to two simple steps: a standard multinomial logit model with no spatial dependence followed by a two-stage least squares estimation of the linearized model which accounts for the spatial dependence. The methodology extended within this paper is relevant to a myriad of empirical problems in addition to land-use decisions. For instance, it can be employed to model household and firm location decisions, occupational choice (based on "economic distance" measures), fishing location decisions, among others.

Monte Carlo simulations indicate that the proposed estimator performs reasonably well. We also compare our results to estimates from a standard multinomial logit model. Preliminary empirical results suggest that the location of new urban development is guided by a preference over lower density areas, yet in proximity to current urban development. In addition, we find very significant evidence of spatial dependence in land use decisions.

Economic Model of Land Use Conversion

To develop the economic model of land use conversion we follow an approach that models land use changes explicitly (e.g. McMillen, 1989; Bockstael and Bell, 1997; Landis and Zhang, 1998; Irwin and Bockstael, 2002; Carrión-Flores and Irwin, 2004). Several assumptions need to be made to develop this model. Consider an economic agent (the landowner) that makes an inter-temporal decision regarding the conversion of a parcel of land to some alternative economically viable use. The landowner is assumed to choose an optimal allocation of land uses such as to maximize the present discounted sum of the expected stream of future net land returns. The returns to conversion are measured net of conversion costs and are a function of land attributes. For instance, land attributes associated with agricultural use may include land characteristics and land quality such as soil type, slope, fertility level, water-holding capacity, location, proximity to market, etc. In the case of residential or commercial land use, the expected returns may be a function of distance to urban centers, employment, shopping sites, neighborhood amenities, public services and policies, etc.

Since only a number of factors that affect the stream of returns and the cost of conversion are observable to the analyst, the net returns can be modeled as having a systematic portion and a random unobservable portion. Let Y_{ik} denote the net returns from a parcel of land *i* currently in use k, X_{ik} denote observed parcel characteristics, and Z_{ik} denote parcel characteristics that affect conversion costs. The land net returns for parcel *i* in use k are given by:

$$Y_{ik} = f(X_{ik}) + e_{ik}$$

where e_{ik} is a random error term representing the unobserved parcel characteristics.

The landowner will choose to allocate parcel *i* currently in use *k* to use l if:

$$Y_{il}(X_{il}) > max_{l \neq k}\{Y_{ik}(X_{ik}) - C_{ik}(Z_{ik})\}, \text{ for all } l=1, \ldots, L$$

Thus, parcel *i* will be converted to use l if the expected net returns from use l exceed the expected returns from the current use *k* and from any alternative use in the choice set *L*. If the inequality does not hold for any uses in the choice set *L*, parcel *i* will remain at state *k.*

This treatment of the net returns implies a latent variable representation of the problem. Consider the "true" net returns for each land use *k*: $Y_{ik}^{*} = f_{ik}(X, Z) + \varepsilon_{ik}$, where *X* and *Z* are observed but not Y^{*}. Then, a parcel of land will remain in use *k* if $Y_{ik}^{*} > Y_{il}^{*}$ for all $k \neq l$ and be converted otherwise to a land use choice that satisfied the inequality. This reformulation of the optimal land use decision can be interpreted in the context of a pressure for conversion and allows for probabilistic statements about the choice of landowner. The model can be directly estimated once a distributional assumption is made for the error term ε_{ik}.

Methodology

The goal is to model the determinants of land use conversion choices. The decision to convert a given parcel from one use to another will depend on several economic factors such as the size of the parcel, its distance to the nearest urban center, its road accessibility, the availability and level of amenities, among other things. In addition, it is plausible that the choice will also depend on the propensity of nearby parcels to choose a particular use (either strategically or collaboratively). For example, a parcel may be less likely to convert to a residential use if it is surrounded by parcels that are likely to be in agricultural use. This feature of the land use decision naturally leads to dependence over space.

A common approach for dealing with spatial interdependence is to estimate a model with a spatial weight matrix that explicitly accounts for the spatial structure of the neighboring land parcels. This study follows the same approach as other spatially-explicit land use change models estimated at the parcel-level using a discrete choice framework (e.g., Bockstael, 1996; Carrión-Flores and Irwin, 2004; Irwin, 2002; Kline and Alig, 1999; Landis and Zang, 1998). We employ a spatial autoregressive lag model (i.e., a spatially weighted dependent variable) to explicitly model the spatial dependence in the context of a multinomial logit model that allows the analysis of the determinants of land use conversion. While a spatially weighted dependent variable has been incorporated successfully in models where the dependent variable is continuous (e.g. Case et al., 1993; Brueckner, 1998; Brett and Pinkse, 2000; Saavedra, 2000; Fredriksson and Millimet, 2002), a spatially autoregressive lag model remains challenging in a discrete choice framework. The reason is that estimation via maximum likelihood quickly becomes infeasible because the likelihood function involves as many integrals as the sample size.

A number of estimators in the literature provide consistent estimates under spatially dependent data for the binary choice case. These estimators attempt to preserve the estimation structure implied by maximum likelihood by either making simplifying assumptions about the spatial weighting matrix or directly simulating the probabilities under a set of assumptions for the error terms (e.g. Case, 1992; LeSage, 2000; McMillen, 1992, Beron and Vijverberg, 2004). Pinkse and Slade (1998), on the other hand, developed a generalized method of moments (GMM) estimator for a spatial-discrete choice model. However, these approaches are all computationally intensive and also become infeasible with large data sets since they require repeated inversion of an $(n \times n)$ spatial weighting matrix.

Klier and McMillen (2008) propose a spatial logit estimator based on Pinkse and Slade's (1998) GMM estimator for the binary choice model. They propose linearizing the model in a way that allows estimation in two steps: estimation of a standard logit model followed by two-stage least squares. They show using simulations that their linearized spatial logit accurately identifies the coefficient on the spatially lag dependent variable. Importantly, the method does not require the inversion of large matrices and thus can be applied to large datasets—those typically available in microlevel data. In this paper, we extend the linearization methodology by Klier and McMIllen (2008) to a multinomial model. Furthermore, and more generally, our extension also covers the conditional logit and mixed logit models.[1]

More specifically, the spatial multinomial model can be motivated with a random utility formulation (McFadden, 1974) in which the decision maker's utility (or revenue as in the economic model above) from a given alternative is a function of nearby agent's utility and other factors:

[1] The difference between these polychotomous models is as follows. The multinomial model allows only variables that vary over units, while the conditional logit allows variables that vary by choice. The mixed logit model combines the two types of variables.

$$Y_{ik}{}^{*} = \rho \sum_{j=1}^{n} W_{ij}\, Y_{ik}{}^{*} + X_i \beta_k + \ \varepsilon_{ik}\,,$$

where $Y_{ik}{}^{*}$ is a latent dependent variable representing the underlying utility from choosing a given alternative *k*, W_{ij} are elements of the spatial weighting matrix *W*, X_i is a vector of explanatory variables, ε_{ik} is a vector of independently and identically distributed errors, and ρ and β_k are the parameters of interest. The spatial weighting matrix is typically row-standardized such that $\sum_{j=1}^{n} W_{ij} = 1$ for *j* ≠*i*, and $W_{ii} = 0$. The parameter ρ measures the degree of spatial dependence. A ρ>0 (<0) would imply that high values of *Y** for neighboring observations increase (decrease) the value of *Y** for observation *i*. The alternative with highest latent utility is the one chosen by the agent, which is observed. Given an extreme value distribution assumption on the errors, the differences in error terms will also possess the same distribution.

The current model can be written in matrix form as:

$$Y^{*} = \rho W Y + X\beta + \ \varepsilon,$$

while the corresponding reduced form of the model can be written as :

$$Y^{*} = (I - \rho W)^{-1} X\beta + e,\ e = (I - \rho W)^{-1}\varepsilon\,,$$

which results in an error covariance matrix proportional to $V(e) = [(I - \rho W)^{'}(I - \rho W)]^{-1}$. The model structure implies both heteroskedasticity and autocorrelation, which is the reason for standard discrete choice models to be inconsistent. Denote by σ_i^2 the variance of the error terms, that is, the diagonal elements of $V(e)$. Define for simplicity $X_i^{*} = X_i/\sigma_i$ and $X_i^{**} =$

$(I - \rho W)^{-1} X_i^*$; and let $d_{ik} = 1$ if alternative k is chosen and zero otherwise. The current model implies the following probabilities (by individual *i*) of choosing alternative *k*:

$$P_{ik} = P(d_{ik} = 1 | X_i) = \frac{\exp(X_i^{**} \beta_k)}{\sum_k \exp(X_i^{**} \beta_k)}.$$

The present model can in principle be estimated using GMM (as in Pinkse and Slade, 1998) or nonlinear two-stage least squares employing instruments *Z* (more about *Z* later) and the model's gradients with respect to the parameters. The gradients are:[2]

$$G_{\beta_{ik}} = P_{ik}(1 - P_{ik}) X_i^{**}$$

$$G_{\rho_i} = P_{ik}(1 - P_{ik}) \left[H_i - \frac{X_i^{**} \beta}{\sigma_i^2} \Lambda_{ii} \right]$$

where $H = (I - \rho W)^{-1} W X^{**}$ and $\Lambda = (I - \rho W)^{-1} W (I - \rho W)^{-1} (I - \rho W)^{-1}$. Importantly, note that to employ this approach the repeated inversion of large matrices is required since the estimates are obtained through an iterative optimization process, which makes it computationally intensive.

The main estimation insight of Klier and McMIllen (2008) is to avoid the repeated inversion of large matrices by approximating the model—which in itself can be argued to be an approximation to the true model—by linearizing it around a convenient value of the parameters. This value sets ρ = 0, since the gradients above greatly simplify as $X_i^{**} = X_i$ and $\Lambda = W$. The parameter ρ is identified from the remaining term *H* (a function of ρ) in the corresponding gradient.

[2] The derivation of these expressions for the multinomial logit, as well as for the conditional and mixed logit models, are relegated to an appendix available upon request.

In practice, the linearization approach consists of two steps. First, the model is estimated with standard multinomial logit, implicitly linearizing around the estimated multinomial logit estimated parameters and ρ = 0. These values are employed to calculate residuals $\widehat{u_{ik}} = d_{ik} - \widehat{P_{ik}}$ and gradients $\widehat{G_{\beta_{ik}}}$ and $\widehat{G_{\rho_i}}$. In the second step, each estimated gradient is regressed on the instruments Z and fitted values are constructed ($\widehat{\widehat{G_{\beta_{ik}}}}$ and $\widehat{\widehat{G_{\rho_i}}}$). Finally, the coefficients in the regression of $(\widehat{u_{ik}} + \widehat{G_{\beta_{ik}}}'\widehat{\beta_k^{MNL}})$ on $\widehat{\widehat{G_{\beta_{ik}}}}$ and $\widehat{\widehat{G_{\rho_i}}}$ are the estimated parameter values of interest. A remaining issue is the specification of the instrumental variables in *Z*. We follow common practice for the linear spatial lag model (e.g., Kelejian and Prucha, 1998) as done in Klier and McMillen (2008) and specify *Z* to contain the linearly independent columns of $[X \;\; WX \;\; W^2X \;\; W^3X \ldots]$. We call this estimator the spatial multinomial logit (SMNL).

Some Finite Sample Evidence

In order to provide evidence of the performance of the SMNL estimator presented above, we conduct a small-scale Monte Carlo simulation exercise. To do this, we partially follow Klier and McMIllen's (2008) experimental design. We consider four alternatives that make the simulations comparable to our model of land-use in the next section. Taking as starting point the reduced form of the model, we employ a single explanatory variable (X) generated uniformly distributed in the interval (-1,1). The variable is transformed as in the previous section to obtain X^* and X^{**} and subsequently the simulated probabilities are obtained as:

$P_{ik} = P(d_{ik} = 1|X_i) = \frac{\exp(X_i^{**}\beta_k)}{\sum_j \exp(X_i^{**}\beta_k)}$. For these, we set each of the β_k coefficients equal to 1. We vary the value of ρ between 0 and 0.9 in 0.1 increments. To generate the observed individual choices, we generate a uniform (0,1) random variable (u) and set $d_{ik} = 1$ for k=l if $\sum_{k=0}^{l-1} P_{ik} < u < \sum_{k=0}^{l} P_{ik}$ with $P_{i0} = 0$.

We consider a specification of *W* that comes from the empirical application in Flores-Lagunes and Schnier (2009), which is a common specification in practice. It sets $W_{ij} = 1/(dist)_{ij}^{f}$ to be the inverse Euclidean distance between locations *i* and *j*, with *f* a “friction" parameter that we set equal to 2. In this specification, the number of neighbors is controlled by choosing a band that is set to 7, and the matrix is row standardized. This general specification of *W* is also similar to the one employed in the empirical application below.

Table 1 reports the simulation results for the standard MNL model and the spatial MNL (SMNL). All simulations were conducted with a sample of *n=320* and 1,000 replications. The matrix of instruments *Z* is specified as $[X\ WX\ W^2X\ W^3X]$. We report the average bias and root mean-squared error (RMSE) of the three estimated slopes (one is normalized to zero) and the spatial parameter estimated by the SMNL. The results indicate that the performance of the MNL progressively deteriorates as spatial dependence (as measured by ρ) increases. The highest amount of bias of the MNL slopes in our simulations is slightly over 24% for a ρ of 0.9. The RMSE also deteriorates as ρ increases. An obvious disadvantage of MNL is that it does not produce an estimate of ρ.

The SMNL estimator has a relatively similar performance as the MNL estimator regarding the estimation of the slopes, both in terms of average bias and RMSE. However, the

SMNL estimator is somewhat more robust to the presence of spatial dependence relative to the MNL estimator (as expected). Nevertheless, it is somewhat disappointing in these preliminary results that the SMNL does not achieve a markedly better performance in the estimation of the slopes as spatial dependence increases. As for the ρ parameter, our preliminary simulations indicate that it is accurately estimated by SMNL when ρ is zero—which is important since it correctly identifies the absence of spatial dependence—but it is underestimated for other values of ρ (except for ρ=0.9). In fact, the percentage bias (relative to the true ρ is large at between 50 to 70 percent for values of $\rho \in [0.1, 0.5]$ to between 20 to 45 percent for values of $\rho \in [0.6, 0.9]$.

Determinants of Land Use Choice

We are particularly interested in the pattern of new urban development as it occurs in rural-urban fringe areas. The typical pattern of new development in rural-urban fringe areas throughout the U.S. is low-density, land intensive development. The area considered for this study is a rural-urban fringe county within the Cleveland, Ohio metropolitan area that is typical of such development: Medina County (located just south of the City of Cleveland and its suburbs).

To generate parcel-level data, we use a Geographic Information System (GIS) that allows us to generate the relevant set of variables using the geocoded parcels and additional GIS data layers. These additional data layers include 1990 land use (Medina County and Cleveland State University), major roads (Ohio Department of Transportation), soil type (STATSGO), and Census block group boundaries and data from the U.S. Census of Population (U.S. Census Bureau). The major urban center of our study area is Cleveland and so we measure proximity from each parcel centroid to the center of Cleveland via the major roads network (Totdiscle). Local markets are important for urban land uses, therefore, distance to nearest city (Disttonear) is included.

To capture the potential disamenity effects of population on urban development, we measure the density of population in 1990 within the local neighborhood of each parcel (Popdens). To capture localized housing demand from the in-migration of urban residents in the region, we measure the proportion of houses in 1990 (housedens). To investigate whether surrounding land uses confer either positive or negative spillovers, we include three variables that measure the proportion of the surrounding land in residential (Reside), commercial (Commarea) and agricultural (Agarea) land uses respectively as of 1990. We also capture constraints to the density of development from large lot zoning with a dummy variable that is assigned a value of one if the minimum lot size is zoned as three acres or greater and zero otherwise (Largelot). Note that these variables measure, to an extent, some of the potential spatial dependence. Whether they are enough for that purpose can be seen from the statistical significance of the estimate of the spatial lag parameter in the SMNL model.

For our spatial analysis, we specify a spatial weights matrix, *W*. Because the true specification of *W* is unknown, six different weighting matrices were constructed that impose varying assumptions about the extent and gradient of spatial dependence. All of them set the non-zero elements of the matrix to $W_{ij} = 1/(dist)_{ij}^{f}$ which is the inverse Euclidean distance between locations i and j, and f a “friction" parameter. The first three specifications of W set the friction parameter to one and consider maximum cut-off distances—beyond which $W_{ij} = 0$—at 400, 800 and 1600 meters. The next three specifications set the friction parameter to two (inverse of the squared Euclidean distance) and employ the same cutoff distances as before. All matrices set $W_{ii} = 0$ and are row standardized (rows sum to one).

Preliminary estimated parameters for the MNL and the SMNL are presented in Table 2, in which the base category chosen is the industrial land use. At this point, we have not computed marginal effects for these estimated parameters—which is undoubtedly of interest—and thus we concentrate in this draft on the point estimates. The estimates from these models tell a consistent story that is in accordance with expectations. Moreover, most estimated coefficients are reasonably robust across specifications. The estimates show that industrial land uses become less attractive as distance to Cleveland (Totdiscle) increases. For instance, the relative probability of a parcel in industrial land use increases as the distance between Cleveland and the parcel decreases. At the same time, local markets are important to agricultural, commercial and residential land uses, as measured by the distance to the nearest town (Disttonear). Estimates indicate that the relative probability of commercial, residential and agricultural land uses is higher than for industrial land use as distance to nearest town decreases.

Land characteristics of the parcel and characteristics of the surrounding area strongly affect the probability of agricultural use. For example, parcel size (Area) has the expected sign indicating that if parcel size increases, the relative probability of commercial and agricultural land uses is higher than industrial land use. On the other hand, the relative probability is lower between residential and industrial land uses as the parcel size increases. In addition, these estimates suggest that the relative probability between agricultural and industrial land use is higher when the majority area surrounding the parcel is in agricultural use (Agarea). Conversely, when urban uses surround the parcel (Reside and Commarea), the relative probability between agricultural and industrial land use is lower. These results are robust across all models presented.

Population density (Popdens) is found to increase the relative probability of agricultural, commercial and residential land uses relative to industrial in all our estimations, implying that these land uses will occur in more dense areas. The magnitude of this effect is fairly small however. House density (Housedens), surprisingly, lowers the relative probability between residential and industrial land uses. This appears counterintuitive, since we would expect that urban development tends to cluster and that, ceteris paribus, urban development is less likely to occur in rural areas. This point merits further investigation. Another measure of proximity to local markets is per capita income (Percpinc). Our estimates suggest that the relative probability of agricultural land use is lower relative to industrial land uses the higher Percpinc is. This is expected since agriculture land use tends to occur in economically depressed areas.

A binary variable representing large minimum-lot zoning (Largelot) is introduced as a land use policy variable. It is defined as a minimum lot size of three or more acres. Estimates suggest that the minimum-lot size policy decreases the relative probability of industrial land use relative to the other land uses, implying that if the parcel is subject to a restriction of a minimum lot size of three or more acres, the industrial land use is less likely to occur.

Our estimates also include indicator variables for the township the parcel is located in, although their estimated parameters are not presented in the table for readability. All of these parameter estimates are positive, indicating that a parcel located in any one of these townships is more likely to experience industrial development than a parcel located in the township to which we normalized the results: Homer Township. This is expected since, in contrast to most of the other townships, the base township is very rural and has experienced almost no urban growth.

Finally, the estimates of the spatial lag parameter (ρ) that is produced by the SMNL model varies from 0.14 to 0.41 (depending on the specification of W), and they are all highly statistically significant. This strongly suggests the importance of a positive spatial interaction effect in land-use decisions. This result is consistent with the widely accepted idea that land use change is a process. Moreover, the presence of these spatial spillover effects suggests that policies at a small scale could lead to a sub-optimal land use pattern. In this regard, the extension of our analysis to the prediction of land use patterns accounting for this spatial dependence is an important next step and is at the top of our research agenda.

Conclusion and Future Work

This paper has presented preliminary results on the estimation of the determinants of land use change employing a multinomial logit model that explicitly accounts for spatial dependence in the form of a spatially lagged dependent variable. The main insight gained with this application is that spatial dependence is an important factor to take into account when analyzing land use choices and conversion. Spatial dependence is critical in these models since it helps us understand the underlying mechanisms of land use predictions. In addition, we corroborate some of the previous findings in the literature in that the location of new urban development is guided by a preference over lower density areas, yet in proximity to current urban development.

A methodological contribution of this paper is the extension of the linearization methodology by Klier and McMillen (2008)—originally applied to a binary logit model—to a multinomial logit model. We present some finite sample evidence on the performance of the method that indicates its promise and points out some areas where further exploration is needed. We remark that this spatial multinomial logit (SMNL) can also be employed in the context of the conditional and mixed logit models to account for spatial lag dependence. All of these models have a wide applicability in analyzing economic decisions.

Several improvements are at the front of this ongoing research. First, it is the need to calculate marginal effects for our SMNL. Their computation is straightforward but somewhat time consuming given that the ($n \times n$) matrix $(I - \rho W)$ needs to be inverted for each specification of W. The second is the application of our SMNL estimates to the prediction of land use changes and its comparison to the predictions given by the standard MNL model. We expect that accounting for spatial dependence results in improved prediction of future land use changes, which is an important input in the development of effective policies. A third aspect is the application of tests for spatial dependence (e.g., Kelejian and Prucha, 2001) to test the model specification by assessing whether a spatially lagged dependent variable is enough to account for all spatial dependence in a given application. Finally, a more complete exploration of the finite sample properties of the SMNL estimator (such as considering larger sample sizes) is warranted given the promising but not completely satisfactory results from the current small-scale Monte Carlo simulation.

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Table 1. Simulation Results for a Sample of 320 Observations

	Standard Multinomial Logit			Spatial Multinomial Logit			
ρ	β1	β2	β3	β1	β2	β3	ρ
0							
Bias	-0.001	0.003	0.005	-0.001	0.003	0.005	-0.016
RMSE	0.080	0.084	0.080	0.080	0.085	0.080	0.248
0.1							
Bias	-0.002	0.002	0.004	-0.002	0.003	0.004	-0.077
RMSE	0.081	0.083	0.079	0.081	0.084	0.079	0.253
0.2							
Bias	-0.003	0.001	0.003	-0.004	0.002	0.003	-0.137
RMSE	0.081	0.084	0.080	0.080	0.084	0.080	0.266
0.3							
Bias	-0.006	-0.002	0.001	-0.006	-0.001	0.001	-0.188
RMSE	0.081	0.083	0.080	0.081	0.083	0.080	0.288
0.4							
Bias	-0.009	-0.007	-0.003	-0.009	-0.006	-0.003	-0.235
RMSE	0.080	0.083	0.079	0.080	0.083	0.079	0.315
0.5							
Bias	-0.019	-0.013	-0.011	-0.018	-0.012	-0.011	-0.261
RMSE	0.080	0.084	0.079	0.080	0.084	0.080	0.342
0.6							
Bias	-0.029	-0.024	-0.023	-0.028	-0.022	-0.022	-0.278
RMSE	0.082	0.085	0.080	0.082	0.086	0.080	0.362
0.7							
Bias	-0.050	-0.044	-0.044	-0.049	-0.042	-0.043	-0.258
RMSE	0.083	0.086	0.080	0.082	0.086	0.080	0.383
0.8							
Bias	-0.097	-0.093	-0.092	-0.095	-0.090	-0.090	-0.162
RMSE	0.089	0.092	0.086	0.089	0.092	0.086	0.396
0.9							
Bias	-0.241	-0.237	-0.239	-0.238	-0.233	-0.236	0.211
RMSE	0.132	0.136	0.135	0.131	0.135	0.134	0.699

Notes: Results based on 1,000 replications. See text for the specification of *W* in the SMNL model. The slope's true value is 1 in all cases.

Table 2. Multinomial Logit (MNL) and Spatial Multinomial Logit (SMNL) Estimated Coefficients of Land Use Change Model

		MNL Results		SMNL Results											
				W_400_f=1		W_800_f=1		W_1600_f=1		W_400_f=2		W_800_f=2		W_1600_f=2	
VARIABLE		Est.	St. Err.	Est.	St. Err.	Est.	St. Err.	Est.	St. Err.	Est.	St. Err.	Est.	St. Err.	Est.	St. Err.
Acres:															
	β*ag*	0.081	0.009	0.090	0.004	0.108	0.004	0.125	0.003	0.090	0.004	0.109	0.004	0.126	0.003
	βres	-0.253	0.014	-0.645	0.072	-0.809	0.058	-0.334	0.041	-0.653	0.072	-0.823	0.057	-0.359	0.040
	β*com*	0.068	0.009	0.068	0.005	0.066	0.004	0.061	0.004	0.068	0.005	0.066	0.004	0.060	0.004
Totdiscle:															
(x10,000)	β*ag*	-0.329	0.083	-0.320	0.024	-0.314	0.024	-0.304	0.022	-0.321	0.024	-0.314	0.024	-0.307	0.022
	βres	-0.355	0.085	-0.402	0.035	-0.414	0.034	-0.345	0.032	-0.405	0.035	-0.419	0.034	-0.345	0.031
	β*com*	-0.381	0.092	-0.386	0.065	-0.383	0.063	-0.371	0.059	-0.386	0.065	-0.381	0.063	-0.371	0.059
Disttonear:															
(x10,000)	β*ag*	0.437	0.163	0.413	0.061	0.348	0.060	0.230	0.056	0.410	0.061	0.345	0.060	0.224	0.056
	βres	0.294	0.171	0.420	0.089	0.467	0.086	0.612	0.080	0.426	0.089	0.484	0.086	0.661	0.079
	β*com*	1.053	0.193	1.102	0.168	1.013	0.164	1.010	0.153	1.094	0.168	0.999	0.163	0.994	0.152
Agarea:															
	β*ag*	1.730	0.807	1.643	0.311	1.452	0.303	1.224	0.283	1.645	0.311	1.447	0.302	1.241	0.282
	βres	1.744	0.835	3.292	0.465	4.054	0.435	3.226	0.392	3.331	0.465	4.093	0.434	3.210	0.390
	β*com*	2.139	1.013	2.199	0.958	2.167	0.931	1.912	0.868	2.187	0.958	2.178	0.929	1.961	0.865
Reside:															
	β*ag*	-1.894	0.929	-1.790	0.373	-1.592	0.363	-1.156	0.339	-1.785	0.373	-1.584	0.362	-1.099	0.337
	βres	4.239	0.955	6.281	0.650	6.776	0.591	2.720	0.519	6.320	0.650	6.818	0.588	2.786	0.515
	β*com*	0.363	1.142	0.517	1.040	0.611	1.011	0.500	0.945	0.527	1.039	0.683	1.010	0.603	0.942
Commarea:															
	β*ag*	-0.007	1.499	-0.089	0.530	-0.070	0.515	0.314	0.481	-0.113	0.530	-0.047	0.514	0.413	0.479
	βres	3.726	1.515	4.938	0.667	5.156	0.638	2.734	0.589	4.925	0.667	5.137	0.637	2.809	0.586
	β*com*	4.545	1.688	4.596	1.191	4.396	1.156	4.094	1.077	4.595	1.191	4.413	1.154	4.130	1.072
Popdens:															
	β*ag*	0.006	0.001	0.006	0.001	0.006	0.001	0.006	0.001	0.006	0.001	0.006	0.001	0.006	0.001
	βres	0.003	0.001	0.002	0.001	0.002	0.001	0.004	0.001	0.002	0.001	0.002	0.001	0.004	0.001
	β*com*	0.011	0.002	0.012	0.003	0.011	0.003	0.010	0.003	0.012	0.003	0.011	0.003	0.011	0.003
Housedens:															
	β*ag*	-0.018	0.003	-0.017	0.002	-0.017	0.002	-0.018	0.002	-0.017	0.002	-0.017	0.002	-0.018	0.002
	βres	-0.011	0.003	-0.011	0.002	-0.012	0.002	-0.014	0.001	-0.011	0.002	-0.012	0.002	-0.013	0.001
	β*com*	-0.034	0.005	-0.035	0.010	-0.034	0.009	-0.032	0.009	-0.035	0.010	-0.034	0.009	-0.032	0.009
Percpinc:															
(x10,000)	β*ag*	-0.352	0.415	-0.361	0.158	-0.329	0.153	-0.276	0.143	-0.361	0.158	-0.323	0.153	-0.283	0.143
	βres	0.036	0.426	0.254	0.212	0.262	0.204	-0.284	0.190	0.246	0.212	0.233	0.204	-0.285	0.189
	β*com*	-1.304	0.495	-1.397	0.433	-1.339	0.422	-1.229	0.394	-1.389	0.433	-1.337	0.421	-1.248	0.392
Largelot:															
	β*ag*	0.650	0.236	0.583	0.087	0.439	0.085	0.223	0.079	0.582	0.087	0.429	0.085	0.220	0.079
	βres	0.144	0.247	0.579	0.156	0.816	0.148	0.495	0.134	0.601	0.156	0.834	0.148	0.511	0.134
	β*com*	0.828	0.266	0.832	0.179	0.804	0.174	0.761	0.162	0.829	0.179	0.800	0.174	0.759	0.161
ρ		--	--	0.145	0.009	0.213	0.008	0.406	0.008	0.145	0.009	0.214	0.008	0.401	0.008

Notes: Sample size is 9,760 parcels. All models include indicater variables for the township in which the parcel resides. The columns for the SMNL estimator correspond to different specifications of W that vary the cut-off distance (400, 800, and 1600) and the friction parameter (f=1 or 2). See text for details.