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Chapter 6

Discrete Choice Model with Structuralized Spatial Effects for Location Analysis

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Abstract: The discrete choice modeling paradigm, and in particular the logit model, are research topics that have been continuously developed and refined for years in the field of transportation applications. Modeling locational choices, on the other hand, differs from modeling transportation choices in that geographically referenced data is used, whereby the choices are specifically spatial. The present paper presents a discrete choice model with a systematic specification of the spatial influences in the choice process. The utility function of the model is specified with autoregressive expressions for the deterministic and error components, and the model is evaluated with reference to three alternative models: the standard logit model, a logit model with an autoregressive deterministic term, and the mixed logit model with autoregressive error terms. Two applications are presented: one with simulated data and another with real data for the analysis of location choice in Sendai City, Japan. The proposed model shows an improved performance over the three reference models.

1. INTRODUCTION

The discrete choice modeling paradigm, and in particular the logit model, have been topics of intense and active research for many years, mainly for applications in the field of transportation choice analysis. Discrete choice models are sometimes distinguished by specifying deterministic and error components of the utility function, according to the purpose of the analysis; different models have been proposed over the years, such as the multinomial logit model, the nested logit model, the mixed logit model, etc. However, the use of discrete choice models for location analysis has received less attention in research and development. Although some of the models used for transportation analysis deal with spatial contexts to some extent [e.g., (Bhat and Zhao 2002) use multilevel methods to model geographical heterogeneity], location choice analysis deals with decisions that could in principle influence each other across space [for a related example dealing with land use change, see (Paez and Suzuki 2001)]. Thus, a key difference with the analysis of transportation choice is that in locational analysis use is made of georeferenced data and therefore of choice sets that have an explicit spatial component. This characteristic of locational analysis requires that special consideration be given to the existence of potentially complex spatial interactions among alternatives and/or decision makers. The objective of this paper is to present a discrete choice model designed for the analysis of location choice, with due attention to the existence of spatial effects.

1.1 Spatial Effects

In the spatial econometrics literature, spatial effects are often discussed from two related but different perspectives, namely spatial dependence and spatial heterogeneity, e.g. (Anselin 1988). Spatial dependence refers to a situation where a variable shows patterns of similarity or dissimilarity across space. If there is a systematic pattern in the spatial distribution of a variable, it is said to be spatially autocorrelated. If, for example, the pattern on a map is such that nearby or neighboring areas are more similar than more distant areas, the pattern is said to be positively spatially autocorrelated. The spatial variation of house prices or household income, are typical examples of positively autocorrelated variables, since wealthy households tend to live in exclusive neighborhoods, segregating themselves from lower income households/residential areas. In a similar fashion, the locational decision of a given agent will likely be determined in part by the decisions of neighboring agents. Spatial heterogeneity, on the other hand, refers to the case when effects, or relationships, are not uniform in space. The spatial econometrician can usually identify this in situations where different model parameters are obtained if different sub-sets of data are used for model estimation. This idea is very similar to that underlying the practice of market segmentation, as in (Ben-Akiva and Lerman 1985), except that segmentation takes place across geographical units. Spatial effects are inherent in data typically used in modeling both the observable explanatory variables, and also the unobservable components of the model; however, in most cases they are not properly treated or sometimes are completely ignored in the analysis of location choice. In other words, there is a need to systematically accommodate spatial effects in a discrete choice model for location analysis.

1.2 Modeling Location Choice when Spatial Effects are Present

Let us consider the residential choice of an arbitrary residential zone, which is located adjacent to a zone which has immeasurable attractiveness. The traditional discrete choice model calculates the zonal utility from zone-specific explanatory variables such as residential convenience, accessibility, etc. However, the zone has the additional benefit of being close to the attractive zone. The benefit, however, becomes smaller if it is located farther away. This clearly exhibits spatial dependence. Therefore, spatial dependency must be incorporated by including the influence of the attractive zone into the utility of the residential zone. From a decision maker's viewpoint, the location choices are available in space, whose attractiveness is reduced with distance. This example clearly shows that the traditional specification of a discrete choice model, based on the attributes of individual alternatives, cannot accommodate situations where spatial effects are active.

Although there are studies that try to incorporate spatial effects in location choice modeling, they are not based on a systematic specification of spatial effects. For example, (Bhat and Guo 2003) presented a mixed logit model where the spatial dependence is modeled with an arbitrary spatial allocation rule. The present paper introduces a discrete choice model with a systematic specification of the spatial influences inspired by the spatial econometrics approach.

2. DISCRETE CHOICE MODELS

Discrete choice models have a long history of application in the economic, transportation, marketing, and geography fields, among other disciplines. For a given individual n, $n=1,\ldots,N$ where N is the number of individual decision-makers, and an alternative i, $i=1,\ldots,J_n$ where J_n is the number of alternatives in the choice set C_n of individual n, the discrete choice model can be written as follows.

$$y_{in}=\begin{cases}1 & \text{if } U_{in}>U_{jn}\text{ , for } j=1,\ldots,J_n \\ 0 & \text{otherwise}\end{cases} \tag{1}$$

$$U_{in}=\mathbf{X}_{in}\boldsymbol{\beta}+\varepsilon_{in} \tag{2}$$

where y_{in} indicates the observed choice, and U_{in} is the utility of alternative i as perceived by individual n. $\mathbf{X}_{in}$ is a $(1\times K)$ vector of observed explanatory variables describing individual n and alternative i such as attributes of the alternatives, socioeconomic characteristics of the respondent, etc. β is a $(K \times 1)$ vector of coefficients and ε_{in} is a random disturbance. These two variables are not observed and treated as stochastic influences. In a compact vector form, ignoring the individual subscript n, the utility equation can be rewritten as

$$\mathbf{U} = \boldsymbol{\beta}\mathbf{X} + \mathbf{e} = \mathbf{V} + \mathbf{e} \tag{3}$$

where $\mathbf{U}$ and $\mathbf{e}$ are $(J \times 1)$ vectors, $\mathbf{X}$ is a $(J \times K)$ matrix, and $\boldsymbol{\beta}$ is as before. The term $\boldsymbol{\beta}\mathbf{X}$ in equation (3) is known as the deterministic or systematic component of the utility function, denoted as $\mathbf{V}$. The logit model results from assuming a particular specification of the disturbance $\mathbf{e}$ in (3), namely, that they are independently and identically gumbel distributed (i.i.d.) across the alternatives. The logit model is referred to as the L model in the numerical example.

2.1 The Mixed Logit Model Framework

An alternative to the conventional logit model is the Mixed Logit Model, see (McFadden and Train 2000). This model results from specifying the disturbance $\mathbf{e}$ in (3) to include a flexible probit-like term (often normal but not necessarily; lognormal or triangular are possible distributions) and an additive i.i.d. gumbel variate, as shown below:

$$\mathbf{U} = \boldsymbol{\beta}\mathbf{X} + \boldsymbol{\xi} + \mathbf{v} \tag{4}$$

where $\boldsymbol{\xi}$ is a $(M \times 1)$ vector of random variables, and v is a $(J \times 1)$ vector of i.i.d. gumbel random variables with zero mean. Denote the density of $\boldsymbol{\xi}$ by $f(\boldsymbol{\xi} \mid \boldsymbol{\theta})$ where $\boldsymbol{\theta}$ are the fixed parameters of the distribution. For a given value of $\boldsymbol{\xi}$, the conditional choice probability is logit, since the remaining error term is i.i.d. gumbel variate:

$$L_i(\xi) = \frac{\exp(\beta' X_i + v_i)}{\sum_j \exp(\beta' X_i + v_i)} \tag{5}$$

Since ξ is not given, the (unconditional) choice probability is this logit expression integrated over all values of ξ weighted by the density of ξ as

$$P_i(\theta) = \int_{-\infty}^{+\infty} L_i(\xi) f(\xi \mid \theta) d\theta \tag{6}$$

This model form is called a mixed logit because the choice probability is a mixture of logit with *f* as the mixing distribution. The probabilities do not exhibit IIA and different substitution patterns are obtained by appropriate specification of *f*. It is, however, worth mention that the mixed logit model may be obtained from another approach (see, for example, (Hensher and Green 2001) and (Train 2003) for details), which is known as random parameter specification. It involves specifying each β associated with an attribute of an alternative as having both a mean and a standard deviation (i.e., it is treated as a random parameter instead of a fixed parameter). Since the standard deviation of a random parameter is essentially an additional error component, the estimation outcome is identical.

3. DISCRETE CHOICE MODELS WITH STRUCTURALIZED SPATIAL EFFECTS

Spatial effects could be accommodated in the discrete choice model by specifying the utility function of equation (3) in various ways, which will result in different models.

3.1 Accommodating the Spatial Effect in the Deterministic Term

It was argued above that in location choice modeling, there are spatial interactions among the systematic utilities among agents locating in different zones. This kind of spatial effect may be accommodated by specifying the utility function in equation (3) such that the deterministic component (or observable part) is spatially autocorrelated. The deterministic term could be expressed in the autoregressive form:

$$\mathbf{V} = \rho_1 \mathbf{W}_1 \mathbf{V} + \mathbf{\beta X} = (\mathbf{I} - \rho_1 \mathbf{W}_1)\mathbf{\beta X} \tag{7}$$

where ρ_1 is the parameter indicating the spatial interaction, $\mathbf{W}_1$ is the spatial weight matrix that defines the pattern of interactions in the system under analysis (the discussion of the spatial weight matrix will be given in following sections), and **I** is the identity matrix. In this manner, with the i.i.d. errors, we obtain a so-called logit model with autoregressive deterministic term (referred to as LAD model in the numerical example). In this case, the utility of other agents in the system enters the utility of individual *n*, and thus conforms to a standard definition of external economies; see (Cornes and Sandler 1996). Note that the autoregressive specification is commonly used in spatial econometrics but has rarely been explored in discrete choice modeling. Alternatively, the researcher may also specify the spatial dependence in the deterministic term differently such as directly specifying the correlation function, which results in the deterministic term $\mathbf{V} = \gamma_1 \mathbf{f}(\mathbf{d}) + \mathbf{\beta X}$ where **f(d)** is a correlation vector as a function of distances between zones **d**.

3.2 Accommodating the Spatial Effect in the Error Term

In similar way to the interaction among spatial utilities, it is possible that there are spatial effects that arise due to missing variables; since the effect of unobservable data is absorbed by the error terms of the model, the result is so-called spatial error autocorrelation. In order to accommodate spatial error autocorrelation, (McMillen 1992) proposed a probit model where the error term **e** in equation (3) in an autoregressive form as $\mathbf{e} = \rho_2 \mathbf{W}_2 \mathbf{e} + \mathbf{u} = (\mathbf{I} - \rho_2 \mathbf{W}_2)^{-1} \mathbf{u}$ where **u** is the multivariate normal random variable vector. Similarly, (Ben-Akiva and Bolduc 1996), presented a mixed logit model (also called a logit kernel model in the literature) that is a special case of an autoregressive error structure. Specifically, the error term ξ of the mixed logit model in equation (4) is $\xi = \rho_2 \mathbf{W}_2 \xi + \mathbf{u}$ where **u** is the multivariate normal random variable vector with mean zero and covariance matrix $\mathbf{S}$. From this framework, if we assume $\mathbf{S} = \sigma^2 \mathbf{I}$ (identical variance for all alternatives), we can define

$$\mathbf{u} = \sigma \boldsymbol{\mu} \tag{8}$$

where σ is a scalar representing standard deviation and μ_i element of the vector $\boldsymbol{\mu}$ is standard normally distributed with mean zero and variance one. Based on this assumption, the error term ξ in the model in equation (4) becomes

$$\xi = \rho_2 \mathbf{W}_2 \xi + \sigma \boldsymbol{\mu} = (\mathbf{I} - \rho_2 \mathbf{W}_2)^{-1} \sigma \boldsymbol{\mu} \tag{9}$$

where ρ_2 is the parameter indicating the spatial autocorrelation, $\mathbf{W}_2$ is the spatial weight matrix, and $\boldsymbol{\mu}$ is the standard normal random variable vector. This model is referred to as MLAE model in the numerical example. Substituting equation (9) into the utility function in equation (4) results in the variance covariance matrix of the disturbance term as

$$\mathrm{cov}(\xi + v) = \sigma^2 (\mathbf{I} - \rho_2 \mathbf{W})^{-1} \left((\mathbf{I} - \rho_2 \mathbf{W})^{-1} \right)' + \frac{\pi^2}{6} \mathbf{I} \quad (10)$$

3.3 The MLADE Model

This paper proposes a model that accommodates spatial effects inherent in the systematic utility as well as in the disturbance term. Specifically, the model combines the concepts in the LAD model in (7) and the MLAE model in (9), to specify the spatially autocorrelated deterministic and error components within a mixed logit framework. In our notation, the deterministic component is specifed as $\mathbf{V} = \rho_1 \mathbf{W}_1 \mathbf{V} + \mathbf{\beta X} = (\mathbf{I} - \rho_1 \mathbf{W}_1)^{-1} \mathbf{\beta X}$ and the random component is specified as $\mathbf{e} = \xi + \sigma\mu + \mathbf{v}$ $= (\mathbf{I} - \rho_2 \mathbf{W}_2)^{-1} \sigma\mu + \mathbf{v}$. The resulting model is therefore a mixed logit model with the autoregressive deterministic and error terms. We call our proposed model as MLADE model. The utility function of the MLADE model is then written as

$$\mathbf{U} = (\mathbf{I} - \rho_1 \mathbf{W}_1)^{-1} \mathbf{\beta X} + \sigma (\mathbf{I} - \rho_2 \mathbf{W}_2)^{-1} \mu + \mathbf{v} \quad (11)$$

where ρ_1, ρ_2 are the parameters indicating spatial effects. In the same manner as equations (5) and (6), the probability of choice of alternative i in the MLADE model maybe written as

$$P_i(\theta) = \int_{-\infty}^{+\infty} L_i(\mu) f(\mu \mid \mathbf{\theta}) d\mathbf{\theta} \quad (12)$$

$$L_i(\mu) = \frac{\exp\left((\mathbf{I} - \rho_1 \mathbf{W}_1)^{-1} \mathbf{\beta X} + \sigma (\mathbf{I} - \rho_2 \mathbf{W}_2)^{-1} \mu \right)}{\sum \exp\left((\mathbf{I} - \rho_1 \mathbf{W}_1)^{-1} \mathbf{\beta X} + \sigma (\mathbf{I} - \rho_2 \mathbf{W}_2)^{-1} \mu \right)} \quad (13)$$

3.4 Estimation of the MLADE Model

The parameters to be estimated in the MLADE model include the scalars ρ_1 and ρ_2 representing the degree of spatial dependency, the standard deviation σ, and the vector $\mathbf{\beta}$ associated with the explanatory variables in the deterministic part of the model. For ease of presentation, we define parameter vector $\mathbf{\theta}$ that includes all parameters in the model. Estimation of the MLADE can be done using the maximum likelihood method, which has commanded substantial attention in recent years , see, for example, (Bhat and Guo 2003). In particular, with n decision makers and i alternatives, the log-likelihood function is

$$L(\theta) = \sum_n \sum_i y_{ni} \log L_i(\theta) \quad (14)$$

$$y_{in} = \begin{cases} 1 & \text{if the } n^{\text{th}} \text{decision maker chooses } i \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

The log-likelihood function in equation (14) involves the evaluation of multidimensional integrals that are not in closed form. The current study employs simulation technique to approximate the multidimensional integrals and maximize the resulting simulated log-likelihood function. This techniques has been used in many literatures; see for example, (Ben-Akiva and Bolduc 1996) and (Bhat 1998).

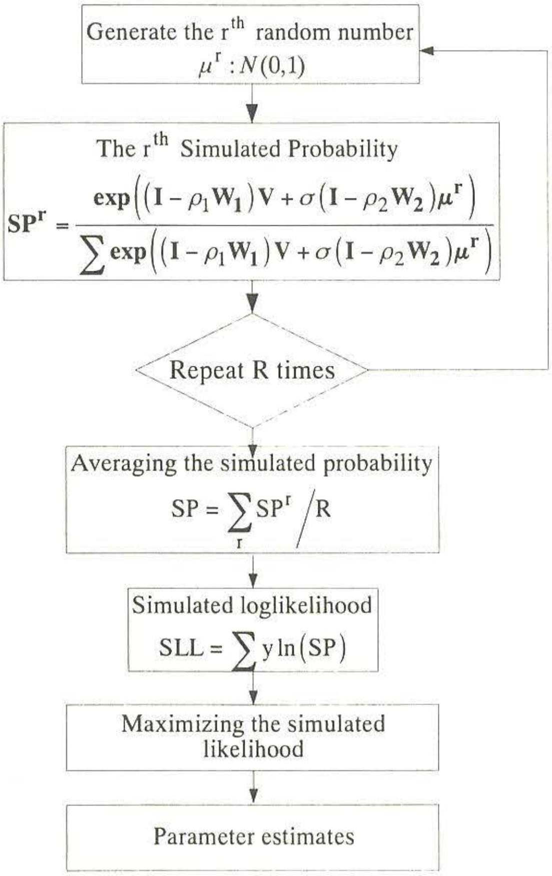

Figure 18 Maximum Likelihood Estimation for MLADE model

As illustrated in Figure 18, the simulation techniques entails computing the integrand in equation (14) at several values of μ drawn from the normal distribution for a given value of the parameter vector θ and averaging the integrand values. Specifically, the choice probabilities are approximated by averaging over the R numbers of simulated probability, as shown in equation (16).

$$\mathbf{SP} = \frac{1}{R}\sum_{r=1}^{R}\frac{\exp\left((\mathbf{I}-\rho_1\mathbf{W}_1)^{-1}\beta\mathbf{X}+\sigma(\mathbf{I}-\rho_2\mathbf{W}_2)^{-1}\mu^r\right)}{\sum\exp\left((\mathbf{I}-\rho_1\mathbf{W}_1)^{-1}\beta\mathbf{X}+\sigma(\mathbf{I}-\rho_2\mathbf{W}_2)^{-1}\mu^r\right)} \tag{16}$$

The above expression is an unbiased estimator of the actual probability. Its variance decreases as N increases. The simulated log-likelihood function is constructed as equation (17).

$$\mathbf{SLL} = \sum_{\mathbf{n}} \mathbf{y}\ \mathbf{ln(SP)} \tag{17}$$

The parameter vector θ is estimated as the vector that maximizes the above simulated function. As discussed in (Bhat and Guo 2003), under rather weak regularity conditions the maximum simulated log-likelihood estimator is consistent, asymptotically efficient, and asymptotically normal. Consult (Train 2003) for the issues of numerical calculation. All estimations in this study were carried out using the GAUSS programming language.

4. VALIDATION USING SIMULATED DATA

In order to validate the proposed model (MLADE), data that exhibit spatial effects inherent in both deterministic and error components is required. For a given zoning system (i.e., the spatial weight matrix **W**'s are given) we produced an artificial dataset by using the data simulator shown in Figure 19, where the resulting choice decision is influenced by such spatial effects.

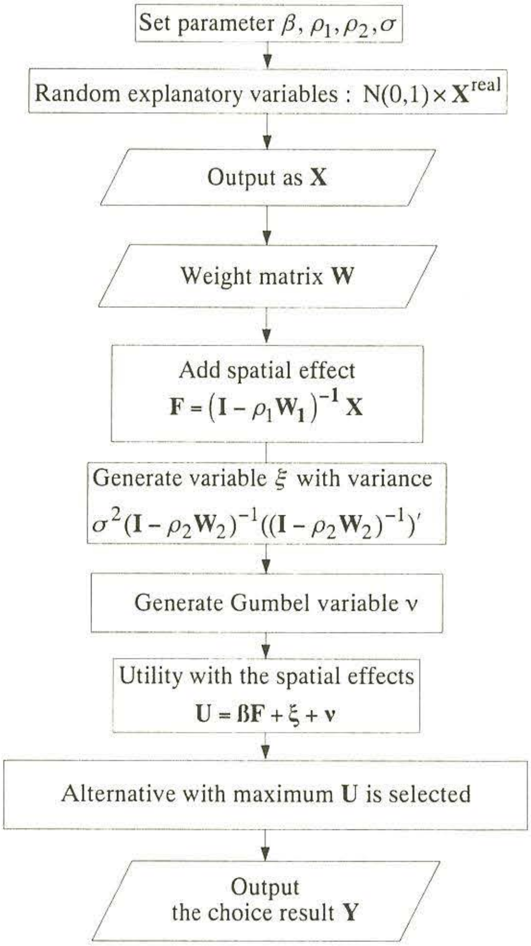

Figure 19 Data Simulator

Briefly, for an arbitrary set of parameters specified (β=6, ρ_1=0.2, ρ_2=0.8, and σ=1 used in this paper), the location choice result **Y** is obtained when the hypothetical decision makers choose the alternative with maximum perceived utility, as influenced by two constructed spatial effects. Firstly, the spatial effect inherent in the deterministic utility is simulated by adding spatial interaction term with parameter ρ_1 to the deterministic component of the utility function as $(\mathbf{I}-\rho_1\mathbf{W}_1)^{-1}\mathbf{X}$. For simplicity, the explanatory variable **X** is a randomly generated number between 0 and 1. Secondly, the spatial effect inherent in the unobservable part is simulated by adding spatial autocorrelation term with parameter ρ_2 to the random component of the utility function, i.e., by generating a multivariate random value with variance $\sigma^2(\mathbf{I}-\rho_2\mathbf{W})^{-1}((\mathbf{I}-\rho_2\mathbf{W})^{-1})'$. A total of 1000 samples are generated for the analysis presented here. We evaluate the four models discussed previously (i.e., L, LAD, MLAE, and MLADE models) by comparing the values specified to the parameter estimates obtained from each model.

Table 2 Parameter Estimation from the Simulated Data

	Specified	L	LAD	MLAE	MLADE
Explanatory ß	6.000	4.133 (21.94)	4.260 (21.67)	4.613 (10.79)	5.219 (14.23)
Spatial Interaction ρ1	0.200	-	0.079 (2.69)	-	0.183 (5.25)
Spatial autocorrelation ρ2	0.800	-	-	0.786 (3.63)	0.950 (3.59)
Standard deviation σ	1.000	-	-	0.474 (0.83)	0.170 (0.18)
Log-likelihood	-	-1020.32	-1017.36	-1017.39	-1008.25
Adjusted likelihood ratio	-	0.264	0.266	0.266	0.272

Table 1 shows the estimation results and the associated t-statistics in parentheses. In general, the three models with spatial effects accommodated have better performance than the standard logit (L) model, i.e., closer parameter estimates to the pre-specified value for β and ρ's estimated. The estimate of σ for MLAE and MLADE are, however, both not statistically significant. Nevertheless, the log-likelihood as well as the likelihood ratio indicates an improved model performance resulting from incorporating spatial effects in the models. More specifically, the MLADE model, which accommodates for spatial interaction and autocorrelation, has an edge over the LAD and MLAE models, which specify either of these effects. It is therefore judged that the gains in performance by the MLADE model offset the slight increase in estimation complexity and cost. Next, the model is applied to a case study.

5. A CASE STUDY OF LOCATION CHOICE IN SENDAI

In the empirical analysis, we apply the four models to a case study in Sendai City of Japan. The city is located 350 km north to Tokyo and it is the capital city of the Tohoku Region of the country. The problem is location choice of residents to the four specific zones in Sendai City, as shown in Figure 3.

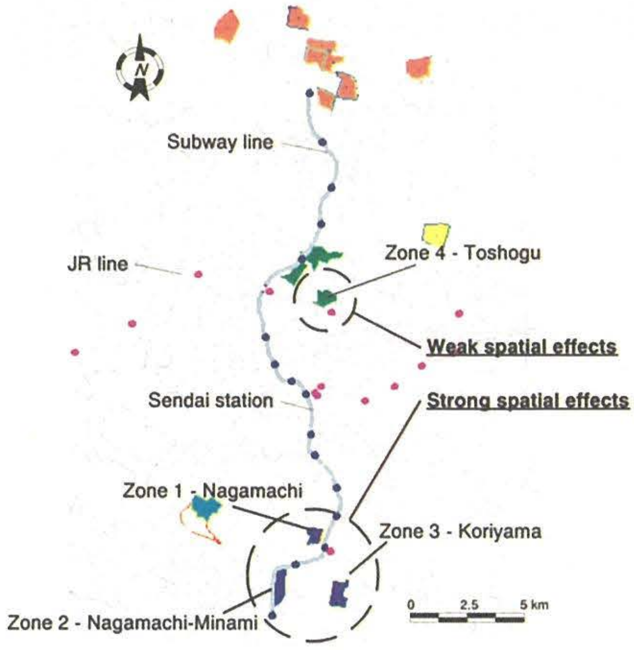

Figure 20 Location Choices of Four Zones in Sendai City of Japan

The city is served with a subway line running in the north to south direction of the city as well as the commuter rail network of the JR railway company. Zones 1, 2 and 3 are located close to each others in the southern part of the city while zone 4 is located remotely in the north. The first three zones entail strong spatial effects while the last one entails weak spatial effects to the location choice of residents. Data used in the analysis is obtained from our original survey conducted in 1996, the official basic land-use survey in Sendai Metropolitan Area in 1992, and the land price survey data in 1992 These data sources provide a rich set of variables for consideration in model specification. In this study, 163 newly moved households locating in the four zones in 1992 were sampled for model estimation. Their housing type is either apartment or condominium. In the other words, the moved households had had choice of residential location and finally located in the corresponding four zones. The explanatory variables corresponding to household movement in 1992 include the number of commercial building, the distance to the nearest railway station in kilometers, the land value measured in relative to individual yearly income, and the zonal heterogeneity measured in various aspects. The zonal heterogeneity in income is measured as the absolute difference between zone-average income and the individual income. The zonal heterogeneity in family size is measured as the absolute difference between zone-average size and the family member in each household. Similarly, the zonal heterogeneity in vehicle holding is measured as the absolute difference between zone-average number of vehicle hold and the number of vehicle in each household.

5.1 Stability of the Estimation

As discussed earlier, the estimation of the MLAE and MLADE models must be done by employing simulation techniques that require generating random numbers. If the number of replication is not large enough, the estimated parameters will not be satisfactorily stable. It is therefore necessary to determine the appropriate number of simulation that yields a stable estimation. We vary the number of simulation and observe the variance of the parameter estimates.

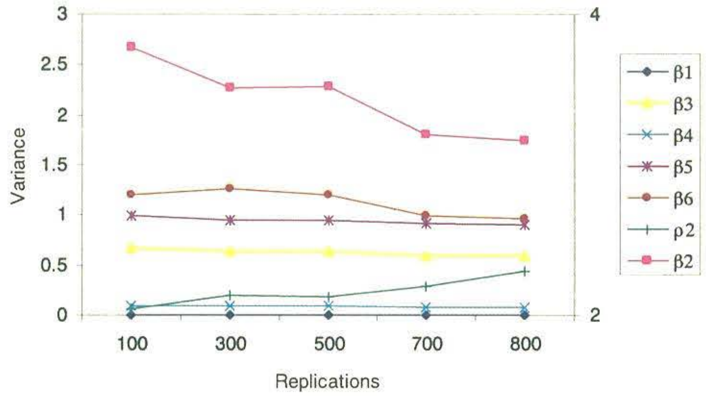

Figure 21 Stability of the Estimation

Figure 21 shows the variance of the estimated parameters β 's and ρ_2 of the MLAE model, which were obtained from different numbers of replication **R**: 100, 300, 500, 700, and 800. The variance decrease as the number of replication increases in most of the variables. It is worth noting that the as the number of repetitions increases the change in the variance of the parameters becomes smaller, thus indicating that stability of the variance has been achieved. Although ρ_2 seems to require more repetitions before achieving stability, at 700 hundred repetitions the results are judged satisfactory considering the parameter's stability. We then use 700 replications for estimating the MLADE model, which is repeated several times and the average value is taken as the parameter estimate.

5.2 Spatial Weight Matrices

The discussion so far has left the spatial weight matrices $\mathbf{W}_1$ and $\mathbf{W}_2$ in equations (7) and (9) unspecified. Matrix **W** represents the relationships among zones of different location in space. The common specification of **W** allows nearby units to be correlated. Various specifications for **W** were proposed; see, for example, (Anselin 1988). The simplest version of **W** may be defined based on contiguity of the zones; 1 if two zones share a common border and 0 otherwise. The other forms of **W**, which are more general in representing the interaction between spatial units, have also been proposed. Mostly, the expressions that represent the distance-decay of the function are used: negative exponential, inverse square distance, etc. A question regarding this matrix of spatial weights concerns the appropriate form for each **W**. Ideally the definition of matrix **W** should follow theoretical considerations. In other words, different definitions of **W** may represent different hypotheses of the operation of the process. We conducted a sensitivity analysis of the functional form of $\mathbf{W}_1$ and $\mathbf{W}_2$ to the estimation results. Two candidates for the specification of **W** are

$$w_{ij} = \frac{1}{d_{ij}^{\alpha}} \tag{18}$$

$$w_{ij} = \exp\left(-d_{ij}^{\beta}\right) \tag{19}$$

where α =2, 3, 4, and 5; and β =1 and 1.5. In total, 6 expressions were used to estimate the LAD and MLAE models and the estimation results are compared. The t-statistic of ρ 's and the likelihood ratio for each expression of w_{ij} are presented below.

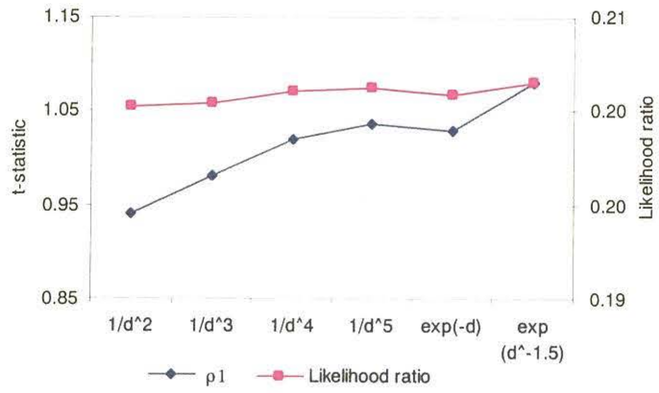

Figure 22 Spatial Weight for the Deterministic Terms (W_1)

In the LAD model, as shown in Figure 22, the higher t-statistic for ρ_1 and higher likelihood ratio is obtained as we move to the right along the horizontal axis. It is obvious that the expression $w_{ij} = \exp\left(-d_{ij}^{1.5}\right)$ is most desirable for the spatial weight matrix $\mathbf{W}_1$.

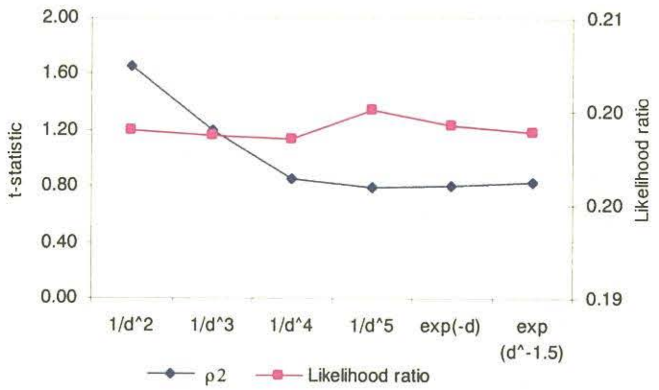

Figure 23 Spatial Weight for the Error Terms (W_2)

In the MLAE model, as shown in Figure 23, we found a decreasing trend of the t-statistic and likelihood-ratio for ρ_2. We therefore judged that the appropriate expression for $\mathbf{W}_2$ is $w_{ij} = 1/d_{ij}^2$, which gives the particularly high t-statistic of the estimate. Therefore, these two expressions of $w_{ij} = \exp\left(-d_{ij}^{1.5}\right)$ and $w_{ij} = 1/d_{ij}^2$ were used for the corresponding terms in the MLADE model.

The model proposed in this paper is expected to accommodate spatial effects in various situations. The definition of distance could be in the simplest case as straight line distance between two points (d_{ij}), with the underlying assumption that space is continuous. This is the approach taken below. On the other hand, straight line distance is just one among a number of possible ways to calculate the separation between points. Needless to say, not all definitions need to assume continuous space. For example, specific applications could use different metrics to reflect various theories about the interactions process, such as distance or travel time over the transportation network; a combination of these to give generalized costs is also a possibility. If, on the other hand, the interest is on the interactions among decision-makers, attendance to meetings, frequency of contact or any such measure of personal interaction could be applied. There is a great deal of flexibility in the possibilities that could be explored. Selection of matrix **W**, on the other hand, poses difficulties of a different nature. As with other spatial applications, for example in the spatial econometrics literature, a definition of matrix **W** in terms of contiguities imposes a rigid structure to the pattern of interactions. Unless the same pattern carries over time, the usefulness of a definition of this type for forecasting purposes might be somewhat impaired to some extent. A definition of interactions in terms of a distance decay function such as above helps to alleviate this problem, because it is not based on a definition of zones, but only on distance between alternatives. The parameters are thus more generalizable, and one needs not worry about changing zoning systems. At this stage, however, our understanding of the implications of selection of **W** for forecasting purposes is sketchy. This is a topic that warrants further investigation.

5.3 Estimation Results

The estimation results are presented in Table 2 where the t-statistics are also shown in the parenthesis.

Table 3 Results of the Parameter Estimation

	L	LAD	MLAE	MLADE
Number of commercial building	0.028 (2.09)	0.037 (2.39)	0.037 (1.46)	0.060 (1.64)
Distance to the nearest railway station	-6.949 (-4.28)	-6.516 (-3.94)	-6.805 (-3.81)	-5.911 (-2.86)
Land price (1,000 yen/m2) / Income (100,000 yen/year)	-2.036 (-2.84)	-1.889 (-2.59)	-2.112 (-2.75)	-1.991 (-2.45)
Difference of household income and the zone-average income	-0.826 (-4.81)	-0.849 (-4.82)	-0.915 (-3.29)	-1.085 (-2.83)
Difference of the number of member in a family and the zone-average number	-1.513 (-1.85)	-1.466 (-1.76)	-1.689 (-1.77)	-1.847 (-1.76)
Difference of the number holding vehicle and the zone-average number	-4.903 (-5.36)	-4.622 (-4.99)	-4.996 (-5.02)	-4.722 (-4.77)
Spatial Interaction (**Error! Objects cannot be created from editing field codes.**)	-	0.013 (1.08)	-	0.018 (1.22)
Spatial Autocorrelation (**Error! Objects cannot be created from editing field codes.**)	-	-	0.874 (1.66)	0.934 (3.21)
Standard deviation (**Error! Objects cannot be created from editing field codes.**)			0.231 (0.22)	0.202 (0.21)
Log-likelihood	-181.20	-180.52	-181.01	-180.06
Adjusted likelihood ratio	0.188	0.191	0.190	0.193

All of the four models give the same sign of parameter estimated, each of which is as expected. Mostly, we obtained relatively larger coefficient of the explanatory variables with the MLADE model. For example, the commercial building has positive effect to the residential location decision as it is intuitive that household tends to locate in the developed area where the necessary facilities are equipped. The MLADE model represents this more pronouncedly. In contrast, the land value in relative to the individual income has opposite effect as can also be imagined; household tends not to locate in the expensive area compared with their income. However, similar households tend to locate close to each other as can be seen from the negative coefficient of the zonal income heterogeneity. Likewise, households with moderately similar size will locate close to each other, again reflected by the negative coefficient of the size heterogeneity. This is due to the fact that the housing developers usually supply similar housing in a certain area. Consider the fact that we rarely find luxurious detached houses mixed with the economical apartment in the village with park and swimming pool. A similar interpretation follows for the heterogeneity in vehicle holding, as the available parking lots as well as the parking charge will be similar in nearby areas. These situations of spatial dependency are effectively captured by the MLADE model with larger coefficients of the explanatory variables, which are statistically significant.

Next, let us consider the correlation coefficients, the significance of the parameters ρ_1 and ρ_2 in the MLADE model indicates the effectiveness of the model structure. However, the estimated standard deviation associated with the normal random error is found to be not significantly different from zero. This could be due to the assumption of identical variance in equation (8). Relaxation by allowing non-constant variance would be able to improve the result and left for the further study. On the other hand, if we consider the improvement of the model capability, it is obvious that the explanatory performance is improved as the model complexity increases. Finally, the results show that the MLADE model has the highest likelihood ratio. The gain is small, but it still hints that structuralized specification of the spatial effects in the MLADE model can help to improve the results.

6. CONCLUDING REMARKS

This paper has shown that spatial effects can be substantially accommodated by the structuralized specification of the utility function in the discrete choice model. The autoregressive expression used has been known and used in the econometrics for a long time, but so far has rarely been explored and employed for discrete choice modeling, in particular in the context of analyzing location choices. A general model that accommodates spatial effects in both deterministic and random components is proposed. Several models can be derived as special cases. The LAD model accommodates spatial effects in the deterministic component while the MLADE model accommodates spatial effects in both deterministic and random components. Although from a conceptual point of view, it is intuitively clear that interactions between decision makers and/or locations should be taken into account as part of the systematic component of the model, in MLADE we opt to include also spatial effects in the error terms. There are two reasons for reaching this decision in the MLADE model. Firstly, in practice it is not wise to rule out the possibility that, in addition to interactions among decision makers, etc., some variables could be missing from the specification. Although part of the spatial effects can be captured by systematic interactions, the effect of missing variables will be to produce error autocorrelation. Thus, the MLADE model is more general, and the analyst has the flexibility to explore for this type of effects in addition to substantive interactions. If, as it may happen, there is no evidence of spatial error autocorrelation, the conceptually more satisfying model with systematic interactions is obtained. And secondly, the MLADE model represents an alternative to more expensive models that incorporate *all* explanatory variables required to account for spatial effects. Needless to say, data collection and modeling efforts may prevent this alternative from becoming a real choice. The MLADE model, on the other hand, can still effectively capture spatial effects even when additional explanatory variables are not available or cannot be easily obtained.

Application of the proposed model using both simulated and real data has confirmed the usefulness of the specification proposed. However, the significance of the results obtained still leaves ample room for improvement, since the present study is limited to a small dataset for the estimation. It is expected that better model performance could be achieved by using an improved and larger set of data. In addition to validation of the proposed model, the above is a matter for further research. As discussed in the introduction, the mixed logit model framework could be motivated by two approaches. This paper has presented an approach based on the error component structure. The results are encouraging for the case of location analysis. The next step will be to apply another approach of the random coefficient in order to allow for heterogeneity in the decision makers since different characteristics of household will exhibit different location behaviors. The difference with (Bhat and Guo 2003) is that spatial dependence will be explicitly modeled with the structuralized spatial effects as MLADE model rather than using spatial allocation rules. The resulting model is a fairly general discrete choice model for the analysis of locational decisions that captures both the spatial dependency and the randomness in the decision maker. This is a topic of ongoing research and additional results will be presented in subsequent papers.

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