A SPATIAL CHOICE MODEL OF CONSUMER BEHAVIOR: ASPECTS OF CALIBRATION AND APPLICATION

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Recently, a number of authors (4, 5, 8, 9, 11, 12, 14) have proposed alternative ways of calibrating spatial choice models of the general form:

\[ p(i | D) = \sum_k U_k \]

where, \( p(i | D) \) = the probability that an individual located at origin \( i \) will choose destination \( j \) from the total set of destinations \( D \);
\( U_j \) = the utility of destination \( j \) as viewed from origin \( i \);
\( f(c_{ij}) \) = a function of the total costs between origin \( i \) and destination \( j \);
\( V_{kg} \) = the value of destination \( k \) on the \( g \)-th attribute, contributing to the attractiveness of the destination;
\( a_g \) = an empirically estimated coefficient for the relative weight of the \( g \)-th attribute contributing to the attractiveness of the destination.

This discussion on the calibration of spatial choice models has been concentrating on the problems of distinguishing the distance-separation effects from the destination effects, on estimating destination effects endogenously from trip distribution data and on problems resulting from different numbers of destinations in the choice set of individuals. The present paper adds a further methodology, in which these three aspects are treated simultaneously, to the existing ones. In addition, the application of the methodology in a study of spatial shopping behavior in South-East Brabant, the Netherlands, will be described.

Methodology

Assume the study area is a closed spatial system, composed of \( N \) mutually exclusive residential zones, called origins, and \( M \) mutually exclusive shopping centres, called destinations. Each origin generates a certain number of shopping trips, \( O_i \), during some finite observation period. Similarly, each destination receives a certain number of shopping trips, \( D_j \), during some finite observation period. Further, let \( t_{ij}^s \) represent the total number of shopping trips

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from origin i to destination j. Then, T denotes the total number of shopping trips within the spatial system and the $N \times M$ matrix of shopping trip frequencies is denoted by $T^s = (t^s_{ij})$.

Our problem is then to derive the relative attractiveness of the shopping centres from observed spatial shopping patterns. Therefore, consider a hypothetical spatial system with only two origins, $O_1$ and $O_2$, and two shopping centres, $D_1$ and $D_2$. The consumers at $O_1$ and $O_2$ must choose between shopping alternatives $D_1$ and $D_2$ at time-distances $d_{11}$, $d_{12}$ and $d_{21}$, $d_{22}$. Figure 1 gives hypothetical values for the relevant variables.

**Figure 1: Hypothetical Spatial System**

Assuming the distances between the two origins and two destinations are equal, the relative attractiveness of the shopping centres is given by the ratio of the total number of shopping trips to the first shopping centre and the total number of shopping trips to the second shopping centre. In formula:

\[
(2) \quad \frac{U_1}{U_2} = \frac{D_1}{D_2}
\]

However, these distances are not equal and this implies that the total number of observed shopping trips is also influenced by the distance separation between the origins and the shopping centres, for example, assume the friction of distance equals $d^2$, $O_1 = 700$ and $O_2 = 950$ and the attractiveness of shopping centre 2 is three times the attractiveness of shopping centre 1. This gives the results presented in Table 1.

**Table 1: The $T^s$ - Matrix**

<table>
<thead>
<tr>
<th>i</th>
<th>j</th>
<th>Destinations</th>
<th>$\sum t^s_{ij}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origins</td>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>400</td>
<td>300</td>
<td>700</td>
</tr>
<tr>
<td></td>
<td>800</td>
<td>150</td>
<td>950</td>
</tr>
<tr>
<td>$\sum t^s_{ij}$</td>
<td>1200</td>
<td>450</td>
<td>$T=1650$</td>
</tr>
</tbody>
</table>

However, until now we have assumed that the attractiveness of the shopping centres is known *a priori*. In practice, the attractiveness of the shopping centres has to be derived from the matrix of observed shopping patterns, presented in Table 1.

This can be accomplished in the following way: First, assume the friction of distance equals $d^2$. This implies that
(3) \[ t_{ij}^s = iA_j^s d_{ij}^{-1} \]

Or,

(4) \[ iA_j = t_{ij}^s * d_{ij} \]

and,

(5) \[ iA_j^* = iA_j / \Sigma_j iA_j \]

and,

(6) \[ A_j^R = \Sigma_i iA_j^* / N \]

where,

\[ iA_j = \text{the attractiveness of shopping centre } j \text{ as seen from origin } i; \]

\[ iA_j^* = \text{the relative attractiveness of shopping centre } j \text{ as seen from origin } i; \]

\[ A_j^R = \text{the average relative attractiveness of shopping centre } j. \]

Table 2 gives the resulting relative attractiveness of the shopping centres for each origin i.

**Table 2: Relative Attractiveness of the Shopping Centres**

<table>
<thead>
<tr>
<th>( i )</th>
<th>( j )</th>
<th>Destinations</th>
<th>( \Sigma_j iA_j^* )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( 1 )</td>
<td>( 1 )</td>
<td>.400</td>
<td>.600</td>
</tr>
<tr>
<td>( 2 )</td>
<td>( 2 )</td>
<td>.572</td>
<td>.428</td>
</tr>
<tr>
<td>( A_j^R )</td>
<td>( .486 )</td>
<td>( .514 )</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Assuming that the attractiveness of the shopping centres is independent of the distance effects, we can iteratively change the friction of distance parameter \( \beta \) until the sum of variances in the column vectors of the matrix of relative attractiveness of the shopping centres is at minimum. Table 3 gives the results by increasing \( \beta \) from -1.5 to -2.5 with steps of 0.5. Evidently, the optimal results are obtained for \( \beta = -2.0 \). The corresponding ratio of the relative attractiveness of shopping centre 1 and 2 equals 1:3; the value initially hypothesized.

Until now, we have assumed that the destinations in the choice set of a residence zone are the same for each residence zone. This assumption might be realistic, for example, for outdoor-recreational behavior but, certainly, it is not for spatial shopping behavior. This is supported by many research findings on awareness spaces, activity spaces, information levels, utility fields and so on (15, 19, 20, 22, 33, 34, 36, 36, 41), indicating the spatially and cognitively discontinuous constrained characteristic of spatial (shopping) behavior. The
Table 3. Results for Different Values of $\beta$.

<table>
<thead>
<tr>
<th></th>
<th>$\beta = -1.5$ Destinations</th>
<th>$\beta = -2.0$ Destinations</th>
<th>$\beta = -2.5$ Destinations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Origins</td>
<td>.320</td>
<td>.680</td>
<td>.250</td>
</tr>
<tr>
<td>A</td>
<td>.400</td>
<td>.600</td>
<td>.250</td>
</tr>
<tr>
<td>$A_j^R$</td>
<td>.360</td>
<td>.640</td>
<td>.250</td>
</tr>
</tbody>
</table>

The problem then is that the methodology, outlined above, no longer is applicable under such circumstances. This is illustrated in Figure 2.

**Figure 2. Hypothetical Example of Different Destinations in Choice Sets.**

Figure 2 shows that choice set I consists of two shopping alternatives, A and B and that choice set II consists of three shopping alternatives, viz. A, B and C. Assuming the attractiveness of the three shopping alternatives is equal, the relative attractiveness of shopping alternative A in choice set I will be 0.5, whereas the relative attractiveness of shopping alternative A in choice set II will equal 0.33. Evidently, using the objective function of minimizing the sum of variances in the column vectors of the matrix of the relative attractiveness of the shopping alternatives for each residence zone will lead to uninterpretable or even wrong results in this situation. Therefore, we will have to specify an objective function which does give interpretable values for the relative attractiveness of the shopping alternatives under these circumstances. One possibility is to minimize the sum of variances in the ratios of the relative attractiveness of the shopping alternatives for all relevant combinations of shopping alternatives. Using this objective function, the ratio of the relative attractiveness of shopping alternatives A and B in choice set I (0.5 : 0.5) will be equal to the ratio of the relative attractiveness of shopping alternatives A and B in
In practice, however, we will probably not get a perfect fit of the model, this leading to different values for the relative attractiveness of the shopping alternatives from each residence zone. Therefore, we will have to derive an average relative attractiveness measure for the shopping alternatives. Given the objective function, the most useful way of deriving the average relative attractiveness of a shopping alternative is to compute the geometric mean of the relevant values for the relative attractiveness of a shopping alternative.

The fact that the geometric mean gives better results in the context of different destinations in the choice sets of the residence zones is illustrated in the next example. Let the attractiveness of shopping alternative $A$ in choice set $I$ be two times the attractiveness of shopping alternative $B$ in choice set $I$ and let the attractiveness of shopping alternative $B$ in choice set $II$ be two times the attractiveness of shopping alternative $A$ in choice set $II$. For example,

1. $A^*_A = .6$  
2. $A^*_A = .2$  
1. $A^*_B = .3$  
2. $A^*_B = .4$

The best decision a researcher can make in this situation is to consider the attractiveness of the two shopping alternatives as equal. However, this is not reflected in the values of the arithmetic mean, which was computed in our initial example, since these values are respectively .4 and .35. Computing of the geometric means, however, results in respectively .346 and .346. That is, the geometric means indicate that the average relative attractiveness of shopping centre $A$ equals the average relative attractiveness of shopping centre $B$.

Summarizing the methodology, the starting point is a spatial choice model of the general form:

\[
\begin{align*}
\pi_D(j | D) &= \frac{\sum_{g=1}^{M} A_j^*}{\sum_{g=1}^{M} A_g^*}, \quad g \in U_i, \\
& \quad j \in U_i \\
\pi_D^{j, k}(j | D) &= \left[ \frac{\sum_{k=1}^{r} \gamma_k V_{jk} / f(d_{ij})}{\sum_{g=1}^{M} \sum_{k=1}^{r} \gamma_k V_{gk} / f(d_{igg})} \right], \\
& \quad g \in U_i, \quad j \in U_i.
\end{align*}
\]

The solution is obtained by minimizing the objective function:

\[
\begin{align*}
\min_{j=1}^{M-1} \sum_{k=j+1}^{M} \left( \text{var} \left( \frac{A_j^*}{A_k^*} \right) \right), \\
& \quad g \in U_i, \quad j \in U_i, \quad k \in U_i, \\
& \quad i=1, \ldots, N
\end{align*}
\]

with
(9) \[ A_j = t_{ij} \times f(d_{ij}) \]

and

(10) \[ A_j^* = \frac{A_j}{\sum_{g \in U_i} A_g}, \quad j \in U_i \]

The average relative attractiveness of the shopping alternative is derived as:

(11) \[ A_j^R = \left( \prod_{j=1}^{N} A_j^* \right)^{1/N}, \quad j \in U_i \]

where,

\[ jP(j|D) = \] the probability that a consumer located at \( i \) selects shopping alternative \( j \) from the total set of shopping alternatives \( D \);

\[ A_j = \] the attractiveness of shopping alternative \( j \) as viewed from residence zone \( i \);

\[ A_j^* = \] the relative attractiveness of shopping alternative \( j \) as viewed from residence \( i \) (\( \sum_j A_j^* = 1.0 \));

\( U_i \) = the utility field of residence zone \( i \);

\( V_{jk} \) = the value of the \( k \)-th attribute of shopping alternative \( j \);

\( f(d_{ij}) \) = a function of the distance separation between residence zone \( i \) and shopping alternative \( j \);

\( t_{ij} \) = the total number of shopping trips from residence zone \( i \) to shopping alternative \( j \);

\( A_j^R \) = the average relative attractiveness of shopping alternative \( j \);

\( M \) = the total number of shopping alternatives;

\( N \) = the total number of residence zones;

\( r \) = the total number of attributes, contributing to the attractiveness of a shopping alternative;

\( \gamma_k \) = an empirically estimated coefficient for the relative weight of the \( k \)-th attribute, contributing to the attractiveness of a shopping alternative.

**An Application**

The model and calibration procedure, outlined in the foregoing paragraph, was used in a study of spatial consumer behavior for durable goods in South-East Brabant, The Netherlands. Within the study area, 33 residence zones and 62 shopping centres were identified.
The input data for the model on observed spatial shopping behavior were collected in two separate surveys. The first survey was undertaken in the summer of 1975 by interview and included 1024 respondents (25), and the second survey was undertaken in the summer of 1978, also by interview and including 771 respondents. These interviews represent about 10 percent of the total number of households in the study area. Although there is a difference of three years between the two surveys, this was not considered problematic since there were no important changes in the retailing structure of the study area in this period. Thus, the two surveys were added together and re-weighted proportional to the relative number of households in each residence zone. The matrix of shopping trips from the residence zones to the shopping centres was constructed by asking each respondent to mention the shopping centres visited as well as the frequency of these visits during a one month time period for a number of durable goods. The purpose of the study then was to model the resulting aggregate spatial shopping behavior patterns in mathematical terms.

The specific form of the spatial choice model used in this respect was:

\[
p(j|D) = \frac{\sum_{g} U_{j}}{\sum_{g} U_{g}}, \quad g \in U_{i}
\]

\[
= \left[ \sum_{k=1}^{r} \gamma_{k} V_{jg} / \left\{ (d_{ij} - d^*_j)^{\alpha} \cdot e^{\beta(d_{ij} - d^*_j)} \right\} \right] /
\]

\[
\sum_{g=1}^{M} \left[ \sum_{k=1}^{r} \gamma_{k} V_{gk} / \left\{ (d_{ig} - d^*_ig)^{\alpha} \cdot e^{\beta(d_{ig} - d^*_ig)} \right\} \right]
\]

(12) \quad j \in U_{i}

\quad g \in U_{i}

where,

\[
d^*_j = \min \{d_{ij}\} + 1, \quad j = 1, 2, ..., M;
\]

\[
a, \beta = \text{calibrated distance parameters}
\]

and the meaning of the other symbols is the same as in the preceding paragraph. Notice that the model describes consumer behavior in terms of the difference of the distance to the shopping centres and the distance, necessary to pass the nearest shopping opportunity. The distances, a consumer has to travel in order to reach the nearest shopping opportunity, are therefore not included in the model. The distance from a particular residence zone to the nearest shopping centre is assumed to represent one unit of measurement. This transformation was thought to be necessary to yield more realistic input data for the choice model. The inclusion of observed distances would imply that the choice set of consumers located in the periphery of the study area is treated differently from the choice set of consumers located in the centre of the study area solely due to the geometry of the study area. In reality, however, consumers located at the periphery of the study area will probably discount the distance to the nearest shopping opportunity and then view the distances to
the more distant shopping opportunities. By taking the difference between the
distances to the shopping centres and the distance to the nearest shopping
centre the input data for the model reflect more correctly the underlying
decision making process of consumers and are partially independent of the
specific geometry of the study area.

The $d_{ij}$ and $d_{ij}^*$ -terms were measured in travel-time units. Firstly, a trans­
portation network, covering the study area, was constructed. Secondly, on the
basis of the spatial distribution of the households within the residence zones,
the speed of the various transport modes on the links of the network and the
distribution of the transport modes for each residence zone, the $33 \times 62$ matrix
of representative travel-times between the residence zones and the shopping
centres were derived.

The identification of the utility fields was based on the observed spatial
shopping behavior patterns in the study area. That is, the utility field of a
residence zone includes the shopping centres, which are patronized from the
residence zone. An alternative and theoretically more valid way of identifying
the utility fields is to derive them from questions in the survey about the
willingness to travel in order to purchase a particular good and the information
levels of the respondents. However, such questions were not included in the
survey of 1975. Therefore, it was not possible to employ this alternative proce­
dure.

Apart from data on observed spatial shopping behavior patterns, utility fields
and travel-time distances, the spatial choice model requires input data on the
attributes of the shopping centres, contributing to their attractiveness. In the
literature (6, 10, 21, 23, 29, 32, 43) numerous attributes, ranging from the price
of the goods and the functional complexity of a shopping centre to the reputa­
tion of the shopping centre and window display, are mentioned. Clearly, not all
these attributes are strictly relevant in a planning context. Therefore, two
criteria were established for the reduced set of attributes to be included in the
model. Firstly, each attribute had to have a direct physical meaning and
secondly the set of attributes selected should encompass the most important
aspects of the physical planning of shopping centres. The reduced set of
attributes consisted of 8 attributes. The list of attributes is given in Table 4.

Table 4: The List of Attributes.

<table>
<thead>
<tr>
<th>Identification</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_1$</td>
<td>Number of parking lots</td>
</tr>
<tr>
<td>$X_2$</td>
<td>Total parking space</td>
</tr>
<tr>
<td>$X_3$</td>
<td>Number of shops</td>
</tr>
<tr>
<td>$X_4$</td>
<td>Number of branches (functional complexity)</td>
</tr>
<tr>
<td>$X_5$</td>
<td>Number of employees</td>
</tr>
<tr>
<td>$X_6$</td>
<td>Number of super-stores</td>
</tr>
<tr>
<td>$X_7$</td>
<td>Number of shops per parking facility</td>
</tr>
<tr>
<td>$X_8$</td>
<td>Index for range of choice per branch</td>
</tr>
</tbody>
</table>
The second part of the study involved the calibration of the spatial choice model. Using the 'sequential linear search' method (1, 2, 3) the model was calibrated on the basis of the objective function of minimizing the weighed sum of variances in the ratios of the relative attractiveness of the shopping centres. The calibrated parameters for the distance function were respectively \( \alpha = .2486 \) and \( \beta = .1510 \). The model accounted for 74.3 percent of the variance in the observed shopping trips and accounted for 99.2 percent of the variance in the number of arrivals in the shopping centres.

The calibration of the time-distance function resulted in a 33 x 62 matrix with the relative attractiveness of the shopping centres as viewed from the residence zones. This matrix was input for the computation of the geometric means, denoting the average relative attractiveness of the shopping centres. The average relative attractiveness of the shopping centres is given in Table 5.

**Table 5. The Average Relative Attractiveness of the Shopping Centres (x10).**

<table>
<thead>
<tr>
<th>Id. no.</th>
<th>Name</th>
<th>Average relative attractiveness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Eindhoven, city centre</td>
<td>6.722</td>
</tr>
<tr>
<td>2</td>
<td>Woensel</td>
<td>1.457</td>
</tr>
<tr>
<td>3</td>
<td>Woenselse Market</td>
<td>0.117</td>
</tr>
<tr>
<td>4</td>
<td>Strijp</td>
<td>0.315</td>
</tr>
<tr>
<td>5</td>
<td>Geldrop</td>
<td>0.297</td>
</tr>
<tr>
<td>6</td>
<td>Valkenswaard — centre</td>
<td>0.983</td>
</tr>
<tr>
<td>7</td>
<td>Woenselse Heide</td>
<td>0.122</td>
</tr>
<tr>
<td>8</td>
<td>Heezerweg</td>
<td>0.473</td>
</tr>
<tr>
<td>9</td>
<td>Tongelre</td>
<td>1.398</td>
</tr>
<tr>
<td>10</td>
<td>Vaartbroek</td>
<td>0.166</td>
</tr>
<tr>
<td>11</td>
<td>Hendrick Staetslaan</td>
<td>0.115</td>
</tr>
<tr>
<td>12</td>
<td>Son</td>
<td>1.486</td>
</tr>
<tr>
<td>13</td>
<td>Breugel</td>
<td>0.185</td>
</tr>
<tr>
<td>14</td>
<td>Waalre</td>
<td>0.211</td>
</tr>
<tr>
<td>15</td>
<td>Aalst</td>
<td>0.421</td>
</tr>
<tr>
<td>16</td>
<td>Leende</td>
<td>1.642</td>
</tr>
<tr>
<td>17</td>
<td>Nuenen</td>
<td>0.774</td>
</tr>
</tbody>
</table>
Table 5 gives the results for only 37 shopping centres. The remaining shopping centres were not important for the purchase of durable goods. These shopping centres were, therefore, not included in the final analysis.

The final part of the study concerned the determination of the relative contribution of the selected attributes of the shopping centres to the derived average attractiveness of the shopping centres. That is, a least squares solution to the attractiveness component of equation (12) is sought in terms of the eight selected attributes of the shopping centres. One way of obtaining these relative contributions is to use stepwise regression analysis. However, due to the problem of multicollinearity, it becomes difficult to sort out the separate relative contributions of the attributes selected.
One possible way out of this problem is to use the ridge regression technique (16, 17, 18, 24, 30, 31). The ridge regression is an estimation procedure based upon

\[(13) \quad \hat{\beta}^* = (X'X + kI)^{-1}X'Y\]

where,

\[\hat{\beta}^* \quad \text{the ridge estimates of } \beta;\]

\[X \quad \text{matrix of standardized independent variables, i.e. attributes of a shopping centre;}\]

\[Y \quad \text{vector of dependent variables, i.e. derived average attractiveness values;}\]

\[k \quad \text{a nonnegative parameter } (0 \leq k \leq 1).\]

Since the estimates \(\hat{\beta}^*\) are not unbiased least squares estimates for \(k > 0\), the error sum of squares associated with \(\hat{\beta}^*\) will be larger than the error sum of squares associated with the ordinary least squares estimates. However, the mean square error of the ridge estimates is smaller than the mean square error of the least squares estimates. The choice of a value for \(k\) can be accomplished by inspection of the ridge trace, a plot of \(k\) against the values of the ridge estimates.

Both stepwise and ridge regressions were run on the data for all 37 observations, with the average attractiveness of a shopping centre as the dependent variable and the eight selected attributes of a shopping centre as the independent variables. Table 6 gives the results for the stepwise regression analysis.

**Table 6. Results of the Stepwise Regression Analysis.**

<table>
<thead>
<tr>
<th>Iteration</th>
<th>Regression Equation</th>
<th>(R^2)</th>
<th>F-test of entire regression</th>
<th>Partial F-tests</th>
<th>Degree of freedom</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>(Y = 0.28138 + 0.00058 X_1)</td>
<td>0.85</td>
<td>192.9</td>
<td></td>
<td>1 and 35</td>
</tr>
<tr>
<td>2.</td>
<td>(Y = 0.16225 + 0.00031 X_1 + 0.00073 X_6)</td>
<td>0.87</td>
<td>109.1</td>
<td>(X_1: 5.7)</td>
<td>2 and 34</td>
</tr>
<tr>
<td>3.</td>
<td>Variable (X_6) was entered. Its partial F-value was 0.27 with 3 and 33 degrees of freedom. The critical F-value at (\alpha = 0.05) is 2.90, so variable (X_6) was not accepted, and the procedure was terminated.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6 shows that only the first two variables entered, contribute significantly to an increase in the multiple correlation coefficient. These two variables are the number of parking lots and the number of employees. Both variables are positively associated with the derived average attractiveness of the shopping centres. Together they account for 87 percent of the variance in average attractiveness scores. Although causal interpretation might be misleading, these results suggest that consumers prefer the larger shopping centres with
good parking facilities for the purchase of durable goods.

The ridge regression results are given in Table 7. Figure 3 portrays the ridge trace. Table 7 again indicates the relative importance of variables $X_1$ (the number of parking lots) and $X_5$ (the number of employees) in explaining the derived average attractiveness scores of the shopping centres.

### Table 7. Results of the Ridge Regression Analysis.

<table>
<thead>
<tr>
<th>k-value</th>
<th>$X_1$</th>
<th>$X_2$</th>
<th>$X_3$</th>
<th>$X_4$</th>
<th>$X_5$</th>
<th>$X_6$</th>
<th>$X_7$</th>
<th>$X_8$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0</td>
<td>0.190</td>
<td>0.071</td>
<td>-0.318</td>
<td>0.044</td>
<td>1.000</td>
<td>-0.062</td>
<td>0.004</td>
<td>0.058</td>
<td>.867</td>
</tr>
<tr>
<td>0.1</td>
<td>0.333</td>
<td>0.034</td>
<td>0.077</td>
<td>-0.024</td>
<td>0.266</td>
<td>0.226</td>
<td>-0.014</td>
<td>-0.034</td>
<td>.838</td>
</tr>
<tr>
<td>0.2</td>
<td>0.295</td>
<td>0.042</td>
<td>0.100</td>
<td>-0.016</td>
<td>0.245</td>
<td>0.231</td>
<td>-0.022</td>
<td>-0.028</td>
<td>.815</td>
</tr>
<tr>
<td>0.3</td>
<td>0.273</td>
<td>0.048</td>
<td>0.110</td>
<td>-0.007</td>
<td>0.235</td>
<td>0.227</td>
<td>-0.026</td>
<td>-0.027</td>
<td>.795</td>
</tr>
<tr>
<td>0.4</td>
<td>0.258</td>
<td>0.051</td>
<td>0.114</td>
<td>-0.000</td>
<td>0.223</td>
<td>0.221</td>
<td>-0.029</td>
<td>-0.028</td>
<td>.776</td>
</tr>
<tr>
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<td>0.054</td>
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<td>.741</td>
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<td>0.058</td>
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<td>0.203</td>
<td>0.203</td>
<td>-0.032</td>
<td>-0.032</td>
<td>.726</td>
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<tr>
<td>0.8</td>
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<td>0.059</td>
<td>0.116</td>
<td>-0.020</td>
<td>0.200</td>
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<td>-0.033</td>
<td>.710</td>
</tr>
<tr>
<td>0.9</td>
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<td>0.060</td>
<td>0.116</td>
<td>-0.023</td>
<td>0.192</td>
<td>0.192</td>
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<td>.700</td>
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</table>

Variable $X_6$ (the number of super-stores) is now also a relatively important variable. Table 7 and Figure 3 also illustrate that the initial values of the regression coefficients alter rapidly as k increases. Variables $X_3$, $X_4$, $X_5$, $X_7$, and $X_8$ even experience a change in sign. Moreover, variable $X_4$ (the number of branches) does not hold its predictive power and could, therefore, be removed from the regression equation. The value of the regression coefficient of the other variables tend to stabilize between $k=0.1$ and $k=0.3$. Hence, we can select a particular value of k within this range; the regression equation then accounts for about 80 percent in the variance of the derived average attractiveness scores of the shopping centres.

### Discussion

The basic objective of this article was to present an alternative approach to the problem of calibrating spatial choice models. Current research on this topic has consistently indicated the problem of the effect of the spatial structure of the study area on the calibrated parameters. That is, the parameters of spatial choice models — and also of spatial interaction and entropy-maximizing models (e.g. 40) — do not describe the spatial behavior of individuals (45, 46). Instead, they simultaneously reflect the spatial behavior of individuals and the spatial structure of the area under investigation.

One possible way out of this problem is to develop alternative models which are calibrated independently of the spatial structure of the study area and therefore truly reflect the spatial behavior of individuals. Rushton’s preference scaling model (13, 26, 27, 37, 38, 39, 42), the information integrating / multi-attributive theory approach (29, 44) and the purely behavioural interaction models (7, 28) have been relatively successful in this respect and surely may become increasingly relevant when formulated explicitly on the basis of a number of planning conditions. However, these approaches still demonstrate certain disadvantages, the most important of which seems to be the fact that
the destination effects must be defined *a priori* and can only be small in number.

A second possible way out of the problem is to concentrate on the discrimination of distance-separation effects and destination-attractiveness effects. The methodology, presented in this article, represents an example of such an approach. Given the assumption of a distance independent attractiveness of destinations, the average attractiveness of destinations may be derived endogenously from trip distribution data. Thus, in this way distance effects are separated from destination effects. In addition, the variables, reflecting certain dimensions of the attractiveness of the destinations, are not *a priori* assumed to be important but are statistically proven to contribute significantly to the attractiveness of the destinations. In this respect, the present methodology is equivalent to the one, presented by Ewing (11) in a study of interstate migration flows in the United States. However, unlike Ewing's approach, the present methodology does not suffer from problems of different destinations in the choice set of the origins and may have some practical advantages. As to the more recently proposed calibration methods for spatial choice models (4, 5, 9), the present methodology might be a possible alternative while it certainly is superior to these methods in that it treats explicitly the problem of a large proportion of zero cells in the trip distribution matrix.

Nevertheless, the methodology, outlined in this article still has some associated problems. One critical aspect of the methodology is the assumption of a distance-independent attractiveness of destinations. Concentrating on the distance an individual has to travel in order to pass the nearest opportunity, implies that the value of the attractiveness of the destinations is the result of the fitted distance function. Therefore, the average attractiveness of the destinations is based on the choice situations of individuals, located in the periphery of the study area as well as on the choice situations of those, located in the central parts of the study area. The question remains whether these different situations form a theoretically sound basis for fitting a distance function. Another problem, associated with the presented methodology is that the statistical properties of some of the parameters are unknown and that the model is calibrated in two successive stages. Considering these comments, it seems desirable to compare the methodology's performance with the other methodologies in specific choice situations.
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