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CONJOINT-BASED CHOICE SIMULATORS: A COMPLETELY DISAGGREGATE APPROACH TO STUDY SPATIAL CHOICE BEHAVIOUR

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The viability of a shopping centre largely depends on its attractivity to consumers and its location relative to the population distribution and relative to other shopping centres. Gravity models, or Spatial Interaction models, have been used for decades as a device to predict the potential market shares for centres from data on these characteristics. Over the years, these aggregate models however have been criticized on several aspects (e.g. Shepherd and Thomas, 1980). One is their limited theoretical base, being largely based on analogies from physics instead of theories about the behaviour of the components that comprise the spatial (retail) systems. Another criticism is that the parameter estimates of these models strongly depend on the covariances and spatial structure in the sample area, and therefore there is limited base for transferring a calibrated model to another area. Also, the models incorporate only few of the variables that are of interest to planners and managers. Finally, the relationships modelled by Spatial Interaction theory are direct relationships between data observed for aggregate units (zones). Application of calibrated models to different zonal structures is therefore relatively difficult.

Two concurrent approaches are discrete choice models and decompositional (or conjoint) preference models. Both are based on an integration of the tradition in micro-economics on individual utility maximizing behaviour (Von Neumann and Morgenstern, 1947; Lancaster, 1971) with psychological theories on perception, attitude and behaviour (Thurstone, 1927; Luce, 1959). The models predict individual choice probabilities. These individual probabilities can be aggregated into any (e.g. spatial) unit of interest, for example to derive market shares, which makes these approaches very flexible. Essentially, these models cannot only be applied at the individual level, but they can also be calibrated for each individual separately, provided there are sufficient data. In this completely disaggregate approach the sample of respondents is respresented by a set of individual choice models. This set can then be applied to predict choices from some set of alternatives. Such a prediction device is called a *choice simulator* (Green, Carroll and Goldberg, 1981). The main advantage of such a device is that this approach maximally accounts for sample heterogeneity because differences between respondents are represented in their different choice model parameters or even in different model structures.

The purpose of this paper is to give an outline of the concept and use of a choice simulator. To give some background first the two utility-based approaches for predicting individual choices, discrete choice models and decompositional preference models, are outlined and compared. The use of discrete choice models appears to be practically limited to the estimation of aggregate choice models, i.e. one parameter set for all respondents. However, as will be shown in the final part of the paper, this modelling approach can be useful to summarize and interprete choice simulator results. The decompositional preference approach is most suitable for the construction of a choice simulator. The choice simulator construction and implementation are illustrated by a review of two studies in which this concept was applied: A study of Louviere c.s. on choice of retirement migration destination (Louviere and Woodworth, 1983; Louviere, 1988) is contrasted with a study by Timmermans c.s. (Timmermans, 1982; Timmermans and Van der Heijden,1984; 1986) on choice of shopping centres. This review shows the wide range of options that is available within the choice simulator framework.

Discrete Choice and Decompositional Preference Models

Recent years have seen an increasing use of both discrete choice models and decompositional multiattribute preference models to study problems of spatial choice behaviour and decision-making. In particular, such models have been used to predict the likely effects of policy measures on individual preferences and choice behaviour. Examples of applications of discrete choice models include such diverse fields as travel mode choice (e.g. Ben-Akiva, 1974), housing choices (e.g. McFadden, 1978), and shopping behaviour (e.g. McCarthy, 1980; Southworth, 1981), whereas applications of decompositional multiattribute preference models in these and other fields are described by e.g. Louviere (1978), Lieber (1979), Recker and Schuler (1981), Timmermans (1982) and Timmermans et al (1984). Applications of both approaches can be found in Golledge and Timmermans (1988).

Both types of models assume that individuals view choice alternatives as bundles of attributes and that they associate the choice of an alternative with a utility value, which is derived from the perceptions of the attributes of that alternative. It is assumed that this cognitive derivation can be represented by an algebraic function of these perceptions or part-worth utilities.

Discrete choice models (e.g. Wrigley, 1985) assume that the utitily (U_r) of an alternative r from a choice set A can be described as the sum of a systematic component (V_r) that represents the attribute values and an error component (e_r) that represents unobserved attributes, individual differences and perceptual error, that is

$$U_r = V_r + e_r$$

It is assumed that the alternative with the highest (unobserved) utility, U_r, will be chosen, so

$$p(r \mid A) = p(U_r > U_{r'}) = p(V_r + e_r > V_{r'} + e_{r'}),$$

where: $p(r \mid A)$ is the probability that alternative r is chosen from set A; U_r, $U_{r'}$ are utilities associated with alternatives r and r'; $\Sigma_{r'}$ is a summation over all r' contained in A.

Assuming utilities U_r to be independently and identically distributed leads to a simple scalable (Tversky, 1972) or IIA-type (Luce, 1959) choice model:

$$p(r \mid A) = U_r / \sum_{r'} U_{r'} \;, \forall\, r,r' \in A.$$

IIA stands for the assumption of 'Independence of Irrelevant Alternatives', which says that the ratio of the choice probabilities of any two alternatives in the choice set is not affected by the availability of other alternatives in the choice set.

In the random utility approach a known and convenient probability distribution is imposed on the error terms, mostly the Gumbel, or 'type I extreme value' distribution which leads to the well-known Multinomial Logit (MNL) model (Manski and McFadden, 1981; Hensher and Johnson, 1981):

$$p(r|A) = \exp(V_r) \;/\; \sum_{r'} \exp(V_{r'}) \;, \quad \forall r, r' \in A$$

The systematic utility component Vr is often assumed to be a linear-in-the-parameters and additive function of the attribute values: $V_r = \beta X_r'$, where β is an unknown parameter vector and X_r' is the vector of known attribute values. However this form is not restrictive as nonlinearities and nonadditivities can easily be defined by extending β and X_r to incorporate the correct quadratic terms or polynomials, resp. to include interaction terms. Even violations of the IIA assumption can be accounted for, by including 'cross-effects', terms that represent the effect of other alternatives on the representative utility V_r (Louviere, 1981; Louviere and Woodworth, 1983). Using weighted least squares or maximum likelihood methods the specified model is calibrated by relating observed choices to values of a priori defined attributes of alternatives. Because the parameter estimates of MNL models are only asymptotic efficient, many observations are required to get satisfactory parameter estimates. This practically limits the discrete choice approach to the estimation of aggregate models, at the best at a segment level.

Other limitations of the discrete choice modelling approach result from the common practice to collect data in a survey. Survey methods permit little control over variation of attribute values and over correlations between attributes. This limits in several ways the possibilities to generalize calibrated models. In the first place, it makes the parameter estimates dependent on specificlevels of other attributes, for example the specific spatial structure of the observed situation. Secondly, the collinearities between independent variables result in inefficient parameter estimates. And thirdly the calibration covers only the alternatives and attribute scores that are available within the present situation, so the model covers only the present domain of experience. As a result, discrete choice models are often not reliable when used to make predictions for new situations, for example when transferred to other spatial structures.

Decompositional multiattribute preference models have been advocated as a possible solution to these problems (Louviere and Hensher,1982; Timmermans,1984a). These models are based on preferences that are expressed in response to descriptions of (potential) real-world alternatives. These descriptions are constructed from attributes that are of interest to the researcher and from attributes that are supposed to be the most relevant characteristics of alternatives in the individual decision-making process. Several methods can be used to determine the latter set of attributes, like factor listing, Kelly's repertory grid methodology, multidimensional scaling or focus groups (e.g. Timmermans et al., 1982).

Levels (fixed values) of these different attributes are then combined according to some experimental design to generate the descriptions of alternatives, called profiles. For example, by combining levels of attributes like distance from the home, assortment, ease of parking and price-image, descriptions of possible shopping centres are generated, like for example "a centre that is at a distance of 10 minutes travel, has a wide selection of goods, is difficult to park, and is relatively expensive". When constructing such profiles care should be taken that no 'odd' combinations of characteristics result, because these lead to unreliable responses. Respondents are requested to state their preference for each of the constructed hypothetical alternatives on some measurement scale, most often a rating scale. The expressed preferences are assumed to reflect the overall utility, U_r, associated with the alternative. Assuming some form of the utility function these responses are decomposed into the contributions ofthe attributes that constituted the factors of the experimental design. To avoid having too many profiles as stimuli, often higher-order interactions in the utility functions are assumed negligible, which permits the use of fractional factorial design to construct profiles, which means that not all possible combinations of attribute levels have to be used (e.g. Montgomery, 1984). Mostly measured utilities are assumed to be interval level, and standard regression techniques are applied. This results in estimates of the average respondent's weighting of the attributes. However, if each respondent completed a full replication of the fractional design, a parameter set could be estimated for each separate individual and a sample of preference equations would be the result, which can be basis for a choice simulator as will be described in the next section.

Concluding, it can be stated that, though both approaches lead to individual models, decompositional preference models are more suitable for the construction of individually calibrated models than discrete choice models. Decompositional preference models require less observations to calibrate an individual model and permit more easily the collection of multiple observations for each respondent (because each respondent can easily judge several profiles). Another advantage of the decompositional methods is that by using experimental design methods the covariance structure of independent variables is completely controlled and there is maximum estimation efficiency. Yet another advantage is that data collection is not limited to currently available alternatives, as data are collected for hypothetical alternatives that are feasible but not per se currently existing. One disadvantage of decompostional preference models is that the external validity of the models has to be considered, though in most of the mentioned applications this validity has proven to be quite good. Another disadvantage is that to predict choice from preferences one has to apply some decision rule, preferably a probabilistic rule, but there is no explicit theory to link preferences to choice and the assumptions underlying momentarily applied rules are difficult to test (Louviere and Timmermans, 1987)

Two illustrative studies that apply a Choice Simulator

The previously described decompositional approach leads to a separate preference equation for each respondent from a sample. The set of equations represents the preference structures of the individuals in the sample in a totally disaggregate form. Such a set of preference equations, together with the set of alternatives that is of interest, constitutes the basis for the choice simulator procedure. The present conceptualisation of a choice simulator is based on the one hand on a study on choice of migration destination described by Louviere and Woodworth (1983, example 6) and Louviere (1988), and on the other hand on a study of Timmermans and Van der Heijden (1986) on consumer choice of shopping centre. Though the essential idea of a choice simulator, which is quite simple, is identical in both studies, they show differences in goals and procedures. The study of Louviere extends earlier conjoint choice-forecasting systems (e.g. Green, Carroll and Goldberg, 1981) to permit the description of the simulated aggregate response surface in a closed-form choice model, like the MNL. The resulting aggregate choice model predicts choice probabilities for a respondent chose at random, given a set of existing or new alternatives. The approach allows for the examination of the validity of the aggregate model, permits the examination of competitive influences over varying choice sets and permits different bases for interpreting the parameters. In the study of Timmermans and Van der Heijden, which builds further upon previous projects on consumer spatial behaviour and urban retail sector developments (e.g. Van der Heijden and Timmermans, 1984; Timmermans et al. 1984), no single aggregate choice model is developed. The study uses the simulation results directly and focuses on the validity of the simulator system and on the use of the simulator as a tool for evaluating scenarios of developments of an existing retail structure. We will outline the construction and implementation of a choice simulator, referring to both studies to illustrate certain aspects and to point at emerging issues.

The set of individual preference functions that underlies a choice simulator was developed as follows. In the study on migration destination, individual preference equations for a sampleof 450 Iowans were estimated from ratings of profiles of migration destinations. The 27 profiles that were rated by a respondent constituted a main effects plan from the 3^{10} factorial of 10 attributes with 3 levels each. The attributes were characteristics like type of location, climate, terrain type, nearness to sea or lake, travel time to close relatives, and others. Levels were formulated as e.g. 'centre of city', 'suburb', or 'rural' for the attribute 'type of location'. In contrast, the Timmermans and Van der Heijden study on choice of shopping centre estimated individual preference equations from ordinal data that were collected from a random sample of 678 Dutch shoppers by means of a trade-off design (Johnson, 1974). The judged hypothetical shopping centres resulted from 5 attributes: choice range, parking facilities, price, atmosphere and travel time, where each attribute was varied over 3 levels, that were mostly defined subjectively (e.g. a bad, average, or good atmosphere). The validity of the estimated linear and additive preference equations was assessed and proved to be good.

After a set of individual preference equations has been estimated from empirical data, it has to be decided what alternatives should be simulated. Alternatives have to be defined in terms of the attributes that underlie the alternatives in the judgement task. If this set included only abstract, generic attributes, only choices between abstract alternatives can be simulated, as a kind of concept testing. However, it is quite possible to incorporate alternative-specific names in the profiles (e.g. Louviere, 1984). This enables the direct prediction of choices among specific, fixed alternatives, as for example modes of transport or existing, named shopping centres. Both the Louviere study and the Timmermans and Van der Heijden study, however, included only abstract categories. The Louviere study used a set of alternatives that was identical to the set in the judgement task. Timmermans and Van der Heijden described real-world shopping centres in terms of the attributes used in the judgement task, assigning levels that corresponded most closely to relevant objective characteristics of a shopping centre. In case of continuous variables one might have interpolated the parameter value. In the study an alternative simulator was constructed in which these descriptions were modified to representplanned changes in the real-world shopping centres.

The two illustrative studies also differ in the way choice sets are constructed. In the Louviere study the 27 migration destinations were put into choice sets of various sizes and composition by way of a 'choice set generating design'. This design treats each profile as a factor with levels 'in the set', resp. 'not in the set' and therefore treatments from this design correspond to different sets of alternatives. The main effects fraction of the 2^{27} full factorial design was used to generate 32 choice sets. In this way the study controls for effects of choice set composition on the simulation results and makes it possible to derive a single aggregate choice model to summarize the simulation results. In the alternative study of Timmermans and Van der Heijden by way of a separate 'information fields' model different choice sets were constructed to account for the fact that not all consumers know all shopping centres in a given region (Potter, 1979; Van der Heijden and Timmermans, 1984).

The simulator is implemented by applying each of the preference equations that are typically maintained in a computer file to each of the constructed choice sets. This leads to a prediction of the separate overall utilities that the respondents from the original sample would derive from each of the constructed alternatives for each choice set. Using some decision rule, it is simulated which alternative a respondent will choose from each choice set. In many applications of decompositional preference models it is simply assumed that an individual will choose the alternative with the highest predicted preference, but, because decision-making is assumed to be a probabilistic process, other decision rules are preferable. The Louviere study applies both the deterministic and a probabilistic, MNL-like, decision rule (and gets almost equal results with both rules). The other study applies a probabilistic choice rule that assumes normal distributed errors, derived in Timmermans and Van der Heijden (1984).

Enumeration of the simulated choices leads to the aggregate response surface that is of interest if one wants to predict market shares. Timmermans and Van der Heijden multiply individual choices with individual expenditures, which were measured in the samestudy, to derive the market shares for each of the shopping centres. However, alternatively the aggregate response surface can be analysed in terms of the factors and subdesigns that constituted the total choice simulation, given the proper designs. Louviere focuses on this feature to develop a single aggregate choice model that predicts probabilities over choice sets and that allows examination of violations of the model's assumptions. The estimation of an aggregate model over choice sets is permitted only if all the choice sets contained a *constant base* alternative during the simulation. This is because only then the attributes can be scaled independently from choice set composition and because then the orthogonality of attribute arrays is retained. When a base alternative is included in each choice set, all the choice frequencies can be converted into odds ratios relative to this base alternative (Theil,1971): Assuming the MNL model, as previously defined, then the log odds ratio is

$$L = \ln(p(r|A) \;/\; p(b|A)) = (V_r - V_b)$$

where b indicates a constant base alternative. Because b is included in all choice sets, in the additive and linear-in-the-parameters form the scaled representative utility term

$$(V_r - V_b) = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k$$

where k is the number of attributes and where choice set effects have differenced out. The constant base alternative can be an abstract alternative defined by the middle levels of the attributes, but it can also be the option not to choose any of the presented alternatives or it can be some real-world alternative. In the empirical part of the study by Louviere respondents were asked to evaluate their present residence with respect to each of the relevant attributes on a scale that was identical to the scale used to measure the preferences for the hypothetical alternatives. In one of the simulations this evaluation of the present real-world situation was included in all the simulated choice sets as a non-choice alternative. Consequently, the resulting choice frequencies were to be interpreted as the probabilities of choosing a particular migration destination relative to staying in the present residence. In this way attributes can be scaled relative to any origin of interest (provided it attracts enough choices to avoid zero-cells) which increases the interpretability and flexibility inthe use of choice simulators.

Conclusion and research question

This paper has been focused on the advantages and problems of disaggregate models and especially on how discrete choice models and decompositional preference models can be used in the construction and use of a choice simulator. A review of the modelling approaches and of two applications showed a range of options possible in the choice simulator framework. In one study the result of a choice simulation was a well-founded single aggregate choice model with parameters that reflect the differences-in-utilities relative to the base alternative that was used in the simulation. The other study derived predictions of market shares for new and existing simulated alternatives, by direct aggregation of the simulated choices.

The main research question that follows from this review is whether, and when, it pays off to construct a choice simulator as described instead of calibrating one preference/choice model for a sample as a whole (which then still could be applied at the individual level). This pay-off depends on the homogeneity of the sample, the importance of having a device that easily can be adapted to predict responses for several different choice sets, with different origins to interprete parameters, and on the importance of low computational costs. And, last but not least, it should be assessed whether, given some budget for data collection, the error increase associated with the estimation of a larger number of (individual) parameters will outweigh the error reduction that results from better accounting for sample heterogeneity.

In this respect the recent development that started with the Louviere and Woodworth (1983) paper should be mentioned toward an integration of, on the one hand, the decompositional approach, with its experimental control and use of hypothetical alternatives, and, on the other hand, the discrete choice tradition, with its focus on the direct modelling of choices instead of preferences. The resulting decompositional choice modelling technique seems a promising approach next to the survey-based discrete choice models and the completely disaggregated choice simulator approach.

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