Retail Change and Individual Choice Dynamics : A Conjoint-based Choice Simulator Experiment

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INTRODUCTION

The effects of retail change on consumer choice behaviour are difficult to predict. This is especially true when the changes involve new shopping centres, or combinations of characteristics of shopping centres, which are beyond the domain of experience. Retail planning practice under such circumstances typically involves extrapolating functional relationships between shopping centre characteristics and consumer choice behaviour, estimated on the basis of survey data. It is not difficult to imagine that such a procedure is prone to relatively large prediction error, especially when substantial change is involved.

Conjoint measurement has been advocated as a possible solution to this problem (Timmermans, 1984). It involves generating hypothetical shopping centres by combining shoppping centre characteristics, some of which may be beyond the domain of experience, and then requesting consumers to express some measure of preference for the resulting set of shopping opportunities. Individual preference structures may then be derived from these data and choices may be simulated by implementing some decision rule, for example that a consumer will choose the alternative which received the highest preference. Since these preference structures relate to hypothetical shopping centres, the effects of retail change on individual choice behaviour and turnover levels of all shopping centres in the study area may be predicted by generating new alternatives which reflect these changes and then simulating choice behaviour by applying the derived preference structures and decision rules to the resulting choice sets.

This paper reports on the application of such a conjoint-based choice simulator in the city of Maastricht, The Netherlands. The data of this study were collected in the context of a structure plan for the centre of the city. The paper itself is organized as follows. First, in the next section the fundamentals of conjoint measurement and conjoint-based choice simulators will be briefly discussed. This is followed by a description of the data, the choice simulator used in the present study and the results of the analyses. The paper is concluded by a discussion of the implications of these findings and some avenues of future research endeavours.

CONJOINT-BASED CHOICE SIMULATORS

Consider a multiattribute choice alternative, for example a shopping centre, which can be described as the ordered m-tuple

$$x = (x_1, x_2, \ldots, x_j, \ldots, x_m)$$

where,

x_j is the level of alternative x on the jth attribute.

Further, assume that an individual´s choice behaviour is the result of his subjective evaluations of the attributes of the choice alternatives, combined into an overall evaluation of each alternative x. Subjects may then be asked to rank the choice alternatives with respect to their overall evaluation. To understand the decision-making process involved it is necessary to identify the composition rule which has been applied in such a task to arrive at the overall evaluation and infer part-worth utilities of the attribute levels. This measurement problem is known as the ´conjoint measurement problem´ and the rule which specifies the composition of the subjective evaluations of the attribute levels is called ´the conjoint measurement model´ (Luce and Tukey, 1964; Krantz, 1964)

Conjoint measurement is thus concerned with simultaneously measuring the joint effect of two or more variables on the ordering of the dependent variable. It typically involves the following steps. First, a measurement model which describes the combination of individual effects is specified. Next, the hypothetical choice alternatives are generated. This step involves identifying the attributes which are considered important in influencing the choice behaviour of interest, defining these attributes in terms of attribute levels, and then combining these into hypothetical choice alternatives according to some experimental design. The choice of design is largely dictated by the chosen measurement model because especially the complex measurement models cannot be estimated on the basis of simple experimental designs. Subsequently, subjects are requested to express their overall evaluation or preference for the resulting set of choice alternatives. These preference measures are then decomposed into the so called part-worth utilities associated with the various attribute levels, given the a priori specified measurement model. The validity of the decomposition may be assessed by calculating some goodness of fit measure. The most appropriate conjoint measurement model for a given decision-making task may be identified by comparing goodness of fit measures for alternative measurement models.

Having derived these preference structures, the next step involves specifying a decision rule which predicts an individual's choice behaviour given the position of the choice alternatives on his subjective preference scale. Actual choice behaviour may then be simulated by defining real-world choice alternatives in terms of the attributes levels incorporated in the experiment, calculating an individual's preference score for each alternative on the basis of the derived preference function and then applying the chosen decision rule to the calculated preferences.

Conjoint-based choice simulators are thus characterized by a set of conjoint equations estimated for individuals that typically are maintained in a computer file. As Louviere (1986) has noted the nature of the choice simulations that can be performed depend to a large extent upon the nature of this file of equations. To understand this, it should be emphasized that the description of conjoint analysis as presented above is only the most simple type of analysis. In recent years much progress has been made in elaborating this methodology. In particular important advances has been made with respect to such issues as the use of more complex experimental designs, estimation methods associated with different methods of measuring individuals' reponses, choice set constraints and the inclusion of choice set composition, dominance and similarity effects. Such developments are discussed at a more detailed level elsewhere (Timmermans, 1984; Timmermans and Borgers, 1985).

The nature of the choice simulations that can be performed depends to a large degree on the following issues (Louviere, 1986):

(a) The nature of the experimental design used to generate the conjoint equations.

The nature of the experimental design affects the type of preference function or choice model that can be estimated. Full factorial designs, which combine the attribute levels in every possible way, allow estimating a wide variety of preference and choice models. In contrast, when a fractional factorial design is used, the nature of the factorial determines the specification of the preference function and the nature of the utility function which can be derived in the choice models. Orthogonal designs only allow estimating the main effects. Nonorthogonal designs usually allow estimating all single attribute main effects and two-attribute interaction effects, but all higher interaction effects are assumed to be negligible and hence are ignored. Likewise, trade-off designs often only allow the estimation of the main effects.

(b) The definition of the choice alternatives

Originally the choice alternatives were constructed by combining the attribute levels according to some experimental design. If the conjoint equations are based on such hypothetical choice alternatives, the simulator predicts choices among abstract, hypothetical alternatives, unless in a separate modelling step the real-world choice alternatives are defined in terms of the attribute levels used in the experiment. Recently, however, some authors have used alternative-specific names in conjoint studies, which enables the choice simulator to predict choices among real-world choice alternatives directly.

(c) The procedure for measuring individuals´ responses.

Most conjoint studies involve a ranking or rating procedure for measuring individuals´ preferences for a set of hypothetical choice alternatives. Strictly speaking, the choice simulator can only predict which of the available alternatives will be chosen, unless one implements a probabilistic decision rule which specifies the probability that an alternative will be chosen, given the preference scores of all alternatives included in the choice set. Recently, however some authors have elicited individuals´ preferences by asking them to express the probability that each of a set of alternatives will be chosen or, alternatively, by letting them choose the one alternative they liked best.

(d) <u>The inclusion of a reference choice alternative.</u> Conjoint models are traditionally estimated on an individual´s ordering of a set of choice alternatives in terms of overall preference. In this case one simulates the probability of choosing an alternative given that a choice will be made. In the more complex applications, however, it is possible to include a non-choice or båse alternative, implying that the simulator predicts the probability of choosing a particular alternative from a choice set that includes a non-choice.

Conjoint analysis and closely related approaches have been successfully applied in geography and urban planning over the last decade in a variety of contexts. Studies in the field of the geography of commercial activities include e.g. Prosperi and Schuler (1978), Schuler and Prosperi (1978), Schuler (1979), Timmermans (1980, 1981),. The vast majority of these studies are concerned with uncovering consumer´s preferences, and involve simple experimental designs and a limited set of shopping centre attributes. Some studies also incorporate an attempt to find the functional relationships between the derived preference function and overt behaviour. To the best of the authors' knowledge, however, studies which use a conjoint-based choice simulator to predict the likely effects of retail change on consumer behaviour are non-existent in geography and urban planning. The present paper is the first which reports on such an application.

STUDY DESIGN AND ANALYSIS.

The choice simulator.

The first step involved in the construction of a choice simulator concerns the specification of the preference model. In the present study the following model was chosen :

$$U_{li} = \sum_{k=1}^{K} \beta_{lkm} Z_{kmi} + \varepsilon_l$$

where,

U_{li} is the overall preference of individual l for the ith alternative;

β_{lkm} is individual l's part-worth contribution of the m-th level of the k-th attribute;

Z_{kmi} is the presence ($Z_{km} = 1$) or absence ($Z_{km} = 0$) of attribute level m of the k-th attribute for the ith alternative;

ε_l is a stochastic error term

This linear additive model can be considered as a formal representation of a compensatory decision-making process in that low scores on some attribute may, at least partially, be compensated by high scores on one or more of the remaining attributes. The summation term of the equation permits such compensation. The model is known to be very robust. It should be noted that the chosen model is rather simple; more elaborate procedures would involve incorporating choice set effects and various context effects. Although one would expect such effects to exist and the predictive results of the complex context-sensitive models appear to be very good, the results obtained with the simpler linear additive model also appear quite promising and, in fact, no study has actually systematically compared the performance of these different models.

The construction of a choice simulator also involves choosing a decision rule which specifies the functional relationship between the derived preference function and overt behaviour. In general different types of decision rules may be considered. The first rule states that an individual will invariably choose the alternative included in his choice set which received the highest preference score. The second rule is more complex and was derived from the following assumptions. First, assume that the preference, U_i, for choice alternative i is a stochastic variable, given by :

$$U_i = \bar{U}_i + e_i$$

where,

$\bar{U}_i$ is the average preference for i;

e_i is stochastic error

If the difference in the overall preferences associated with choice alternatives i and j is then denoted by u_{ij}, it follows that the probability that alternative i will be chosen is given by :

$$p_i = \text{prob}(U_i > U_j)$$

$$= \text{prob}(U_i + e_i > U_j + e_j) \qquad i \neq j;\ \forall j.$$

$$= \text{prob}(u_{ij} > 0)$$

If it is assumed that the errors are described by a multivariate normal density function and that all variances are equal, the choice probability of choosing alternative i then equals :

$$p_i = 1 / \{ 1 + \sum_{j;j \neq i} e(-\Pi u_{ij} / \sqrt{3} s_{ij}) \}$$

where,

s_{ij} is the standard deviation of the difference in overall preference.

It has been found previously (Timmermans and van der Heijden, 1984) that this probabilistic decision rule leads to satisfactory results.

Another important issue in the construction of a choice simulator concerns the definition of the choice set. Almost all previous studies have either explicitly or implicitly assumed that all alternatives present in the study area belong to all individuals' choice sets. Consumers are thus assumed to have identical choice sets. While this assumption may be valid in some contexts, it is well known from the literature that consumers are only familiar with a limited number of shopping centres. Studies on consumer spatial information and usage fields (e.g. Potter, 1979) have indicated that consumers rarely are familiar with more than six or seven shopping centres, and that they typically do not have identical choice sets. Sectoral and distance bias is generally strong. These findings imply that a valid choice simulator should incorporate individual choice sets. In theory it is possible to identify explicitly each individual's choice set by looking at his spatial information or perhaps his usage field, but the disadvantage of such an approach is that it may be difficult to predict individual-level spatial information and usage fields. At the very least the only study conducted so far to predict choice set generating processes (van der Heijden and Timmermans,

1984) has adopted an aggregate approach. It was decided therefore to use a similar approach in the present study. Thus, the definition of the choice sets was based on the following equation which predicts the probability that an individual will be familiar with a particular shopping centre.

$$p_{ij} = \exp(-0.090+1.292X_{j1}-0.885X_{j2}-2.222X_{j3}) \; / \; 1+\exp(-0.090+1.292X_{j1}-0.885X_{j2}-2.222X_{j3})$$

where,

p_{ij} is the probability that an individual at location i will be familiar with the jth shopping centre;

X_{j1} is the size of the jth shopping centre;

X_{j2} is the distance between location i and shopping centre j;

X_{j3} is a variable denoting the presence (=1) or absence (=0) of an intervening opportunity between an individual's home and shopping centre j.

Because the choice simulator is applied to predict the effects of retail change, it is also necessary to model these changes in an interactive framework. Many studies on modelling the effects of retail plans on spatial consumer behaviour have adopted a conditional forecasting approach, implying that the change involved is explicitly defined in terms of the independent variables of the model, which is then used to predict subsequent changes in consumer choice behaviour conditional upon the assumption that the established relationships between the independent variables included in the model and overt consumer choice behaviour remain stable, at least in the short run. In this study, however, an attempt is made to incorporate also reactive behaviour of retailers, when they are faced with changes in consumer behaviour and turnover. This is done by establishing the relationships between the subjective probability that a retailer will be engaged in some type of reaction and the degree of change involved. These functions are described elsewhere (van der Heijden and Timmermans, 1986). Since retailers will have a limited budget for reactions, it is assumed that the maximum budget is dependent of the gains in the previous period. The available budget is transformed into a decrease or increase in floorspace by an empirically known budget to floorspace ratio.It should be noted beforehand that this submodel is too simple and that it should be advanced in future studies.

The simulation thus works as follows. First, the shopping centres are described in terms of the attributes included in the preference experiment. Next, for each respondent separately, a choice set is identified on the basis of the spatial information field, predicted for residential zones. The respondent's preference score for each shopping centre is then calculated by applying his part-worth preference function to the description of the shopping centres in terms of attribute levels. Given these preference scores, actual behaviour is simulated by implementing the deterministic highest preference decision rule. These predicted individual choices are then aggregated across respondents to yield an estimate of aggregate retail turnover. Retail change is then incorporated either by forecasting retailer's reactive behaviours or by defining retail plans in terms of the attribute levels included in the conjoint equation. This results in adjusted attribute levels of the shopping centres involved and hence in changes in preferences and subsequent choice behaviour. This process is repeated iteratively for some fixed time horizon.

The study area.

The study was conducted in the Maastricht region. Maastricht is situated in the south of the Netherlands. Apart from the city centre, the city has 24 shopping centres. In common with the majority of medium-sized towns in the Netherlands, Maastricht with a population of 110.00 in 1981, has experienced quite fundamental retail change over the last decade. A major peripheral shopping centre (Heer) has been constructed, mainly attracting car-based trade. In addition, due to substantial renovation projects and ageing of the population a shopping area close to the city centre, called Oud-Wyck, has lost a considerable amount of spending power, which in turn initiated a process of down-grading and resulted in many closures and low viability rates in this area. On the other hand, much of the population growth in the region was concentrated in an outer sector of the city. New housing projects were largely realized in this sector and this evidently has led to a considerable growth in available spending power in this area, as indicated by high turnover levels of tne shops in this area.

The data.

The data for the analysis were obtained from a randomly selected sample of 678 respondents. The person in the household, who was responsible for shopping, mainly the wife, was invited to complete the questionnaire. The data were collected through personal interviews by experienced interviewers, who were hired locally and trained by a national opinion research compagny. Because some of the measurements were rather complex, care was taken that the interviewers fully understood all measurement procedures. In addition, the phrasing of the questions as well as their elucidations were extensively tested in pilot studies. Respondents were told that their answers would be used to formulate proposals for future retail plans as a means of motivating them.

A variety of data was collected , but for the present anslysis only some of these are relevant. First, actual shopping behaviour was measured by presenting a list of eighteen nondaily goods. For each type of good, respondents were asked to name up to three shopping centres where they buy the particular good, the frequency of purchase and the amount they usually spend. These responses were aggregated across respondents to yield measures of actual choice probabilities and market shares. Second, data on consumer preferences for a set of hypothetical shopping centres were obtained. This of course constitutes the conjoint experiment. The shopping centres were defined in terms of five attributes : choice range, parking facilities, price, atmosphere and travel time. These attributes were selected on the basis of the results of previous projects, which consistently suggested, using different measurement techniques such as repertory grids, factor listings and importance scales, that these attributes are among the most important attributes influencing consumer choice of shopping centres. Each attribute was varied over three levels : choice range varied over limited, medium, and wide range of choice ; parking facilities varied over bad, average and good; price varied over low, average and high; atmosphere varied over bad, average and good and travel time varied over 5, 25 and 45 minutes. A trade-off design was used to measure consumer preferences. That is, (5*4)/2 = 10 trade-off matrices were constructed. Each matrix contains nine cells, each of which represents a combination of attribute levels of the two attributes involved. Respondents were asked to rank all nine combinations of attribute levels from most preferred to least preferred for each trade-off matrix separately. To avoid patternized responses, the order of the attribute levels was varied across pairs of attributes. Each respondent was asked to ascertain that the preference orderings were correct. Otherwise, changing the preference ordering was allowed. They were told that their responses should reflect their preferences when shopping for non-daily goods. This procedure thus resulted in 10 strict rank orderings of hyphothetical shopping centres varying over two attributes only for each respondent.

Retailers' reactions on changes in turnover levels were measured by placing them in hypothetical situations and asking them to express their subjective probability of adopting some type of reaction for different levels of decreases and increases in turnover. These questions were asked for various types of potential reaction, including a non-reaction. Only the data pertaining to the reactions which involve the floorspace attribute were used in the analysis. The sample of retailers was not drawn from the study area, simply because the original study did not include this measurement. The retailers stem from the city of Eindhoven. The inclusion of their data implies the assumption of transferability of retailers reactive behaviour across space. This assumption should be empirically tested in future research, but for the moment this assumption is believed to hold.

Analysis and results.

The first step in the analysis involved estimating the preference function. The part-worth utilities can be estimated by a variety of techniques (Timmermans, 1984). In the present case, standard linear regression analysis was used to obtain the parameter values of the conjoint measurement model. Strictly speaking, this is an invalid procedure since the dependent variable is only measured at an ordinal scale. Several simulation studies have shown however that the results from ordinary least squares are virtually indistinguishable from the results obtained by the theoretically preferable techniques such as linear programming or nonmetric scaling. The disadvantage of the latter techniques is that these are very costly in terms of computing time. Therefore, linear regression analysis was used.

The full data matrix for the estimation of one respondent's preference model consists of 720 observations on 10 independent variables. For the estimation of the part-worth utilities only (M_k - 1) linearly independent variables are needed for each attribute k, where M_k denotes the number of attribute levels of attribute k. Thus, in the present case each attribute can be represented by two indicator variables, yielding a total of 5*2 = 10 independent variables in the regression analysis. Effect coding was used to value the independent variables. This means that for each attribute, a number of coded vectors equal to the number of attribute levels minus 1 (= 2) was constructed and that for these coded vectors values of 1 were assigned to choice alternatives, characterised by an arbitrarily chosen attribute level, values of 0 were assigned to alternatives which were characterised by all remaining attribute levels but one, and values of -1 were assigned to all choice alternatives characterised by the excluded attribute level. The value of the independent variable was set to 0 when that attribute did not appear in the trade-off matrix, corresponding to the observation in the data matrix. Each trade-off matrix generates (9*8/2) = 36 implicit paired comparisons. The value of the dependent was set to 1 for the preferred combination of attribute levels, and 0 otherwise. Hence, each paired comparison yields two observation, implying that in total 10*36*2 = 720 observations were generated. An indication of the goodness of fit of the linear additive main-effects only preference model was obtained by calculating Kendall's tau, a measure which expresses the strength of the ordinal relationship between the predicted and the manifest rank orderings in the trade-off matrices.

The estimation results are given in Table 1. Table 1 shows that the estimation results are satisfactory. 89.3 percent of the respondents exhibit a tau

Table 1. Frequency distribution of tau.

Value of tau	Frequency	Percentage	Cum. Percent
0.0 - 0.1	0	0.0	0.0
0.1 - 0.2	0	0.0	0.0
0.2 - 0.3	0	0.0	0.0
0.3 - 0.4	0	0.0	0.0
0.4 - 0.5	1	0.1	0.1
0.5 - 0.6	5	0.7	0.9
0.6 - 0.7	10	1.5	2.4
0.7 - 0.8	57	8.4	10.8
0.8 - 0.9	218	32.2	42.9
0.9 - 1.0	387	57.1	100.0

value of 0.8 or higher; only 6 have a value of lower than 0.6. The mean tau value is 0.88; its standard deviation is only 0.07.

Further support for the validity of the preference model was obtained by testing whether the estimated preference scales for the various attributes were monotone in a priori anticipated directions. In particular, it was assumed that preference should increase with increasing levels of choice range, parking facilities and atmosphere, whereas it should decrease with increasing levels of price, and travel time. The results are provided in Table 2, which clearly demonstrates the validity of the model. The results indicate that at least 94.1 percent of the respondents have a utility function that is in the anticipated direction. The highest percentage is obtained for the choice range attribute. The relevent percentage is 97.8 %. The lowest results were obtained for the distance attribute, although the percentage of respondents with part-worth utilities in anticipated directions is still 94.1 percent.

A third test on the validity of the preference model consists of a cross-tabulation of the mononicity test across the values of tau. Table 3 gives the

Table 2 Monotonicity test.

Variable	Monotonicity	
	Absolute	Percentage
Choice range	663	97.8
Distance	638	94.1
Price	656	96.8
Parking facilities	654	96.5
Atmosphere	658	97.1

resulting cross-tabulations. It shows that respondents whose part-worth utilities are in anticipated directions also exhibit a high tau value. Only few respondents with high tau values have part-worth utility functions that are not in anticipated directions.

Having estimated each individuals´s preference model, the next step of the analysis involved linking these preferences to observed consumer spatial choice patterns. This step can be considered as a test of the external validity of the preference model. It test whether the derived preference functions are systematically related to overt choice behaviour. This is done by implementing some decision rule. In the

Table 3. Cross tabulation of tau vs. monotonicity.

Tau	Monotonicity Absent		Present	
	absolute	percentage	absolute	percentage
0.0 - 0.1	0	0.0	0	0.0
0.1 - 0.2	0	0.0	0	0.0
0.2 - 0.3	0	0.0	0	0.0
0.3 - 0.4	0	0.0	0	0.0
0.4 - 0.5	1	0.1	0	0.0
0.5 - 0.6	5	0.7	0	0.0
0.6 - 0.7	9	1.3	1	0.1
0.7 - 0.8	24	3.5	33	4.9
0.8 - 0.9	34	5.0	184	27.1
0.9 - 1.0	10	1.5	377	55.6

study a probabilistic rule which states that the of choosing an alternative is given by the multivariate logistic equation, outlined in the previous section of the paper. The implementation of these decision rules necessitates that each of the shopping alternatives should be defined in terms of the attibute levels included in the preference experiment. This can be accomplished along several different lines, but in the present case the following straightforward procedure was used. In case of continuous attributes the actual attribute scores were used; in case of ordinal attribute levels the shopping alternatives were assigned to a particular attribute level by examining their objective characteristics and arbitrarily setting boundaries. Part-worth utilities were then obtained by simple linear interpolation or extrapolation in case of continuous attributes and linear assignment in case of ordinal attributes. The predictive ability of the probabilistic decision rules was assessed by comparing predicted market shares, obtained by aggregating predicted individual choices across respondents, and actual market shares. To avoid interpretation bias, different goodness of fit measures were calculated.

The results of this part of the analysis are given in Table 4. It clearly demonstrates that the predictive ability of probabilistic decision rule is satisfactory. The linear additive main effects only preference function when combined with a probabilistic decision rule accounts for 99.3 percent of the variance in the shopping centre choice probabilities as indicated by the coefficient of determination. Table 4 also suggests a

Table 4. Goodness of fit of the model.

Measure	Value
Coefficient of determination	0.993
Robinson´s agreement measure	0.996
Theil´s inequity measure	0.009
Mean absolute error	0.199

reasonably linear relationship between predicted and actual choice behaviour : Robinson´s agreement measure which measures departures from the the x=y regression line is equal to .996. The mean absolute error is only 0.199.

Effects of retail change

The final part of the analysis concerns the application of the constructed choice simulator to the problem of forecasting the effects of planned and spontaneous retail change on consumer choice behaviour. This type of analysis basically involves a series of operations on a set of computer files. In particular, the simulation is based on the following files :

- a file containing the conjoint equations;
- a file containing consumer information fields;

- a file containing retailers´ reactions;
- a file defining existing retail plans;
- a file containing figures about population development in the identified residential zones of the study area;
- a file containing data about changes in spending power for each residential zone;
- a file containing data about spending power that flows to external zones, respectively that stems from external zones.

The choice simulator described above was applied to a set of planning scenarios that were developed for the city of Maastricht. These scenarios reflect the particular retail problems and expected retail change in this city. As stated before, the shopping area, called Oud-Wyck, experienced very low turnover to floorspace ratios due to the ageing of the population and lower attractiveness. On the other hand, the available retail facilities in the neighbourhood called Heer were low compared to the steady growth of the population in this area. One of the main objectives of the city´s retail planning was to increase the size of this shopping centre dramatically to create a more profound functional hierarchy within the city. The problem here however is that negative feedbacks on Oud - Wyck may be expected because these two areas are located at a close distance. Finally, previous research has indicated that the position of the city centre could be improved by enlarging its retail floorspace.

In total 8 different scenarios were formulated. They are briefly described here :

Scenario 1 focuses on improving the retailing conditions in Oud-Wyck. These improvements basically concern the accessibility for cars and the atmosphere.

Scenario 2 involves a reduction of the floorspace in Oud-Wyck with 4000 m^2.

Scenario 3 consists of a combination of these two scenarios.

Scenario 4 implies the extension of the floorspace in the sector of the non-daily goods in the city centre of Maastricht with 8000 m^2.

Scenario 5 combines scenarios 3 and 4.

Scenario 6 involves an increase in floorspace in the sector of nondaily goods in Heer with 1500 m^2, combines with scenario 1.

Scenario 7 envisages the same development for Heer but now combined with scenario 3 for Oud-Wyck.

Scenario 8, finally, combines scenario 7 with a proposed extension of the floorspace in the city centre with 6000 m^2.

The choice simulator was applied to each of these 8 scenarios and the results, expressed in terms of turnover to floorspace ratios, were compared to a trend development, which was predicted by applying the simulator to the same data, however now without the planned changes in the retail structure. All the results were indexed to the situation in 1980. The findings are given in table 5.

Table 5. Results of the predictions for Oud-Wyck. Turnover to floorspace ratios.

Years	Scenario							
	1	2	3	4	5	6	7	8
1980	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
1985	275.5	106.0	295.3	88.6	256.1	267.9	285.1	258.0
1990	276.6	105.9	297.2	89.2	252.6	269.9	288.1	255.1

Table 5 only provides the results for Oud-Wyck and for three years, but similar results are generated for all other shopping centres and all years included in the analysis. The analysis also results in predicted changes in the characteristics of the shopping centres. The findings of the analysis presented in Table 5 show that the improvement of the attractivity of Oud-Wyck has better effects as compared to a reduction of its floor-space. Apparently, a reduction will not only result in better turnover to floorspace ratios, ceteris paribus, but also in a lower attractivity, implying that fewer consumers actually patronise the shopping centre. The effects of increasing the size of Heer and the city centre are as expected. The scenarios involving these centres have negative effects on Oud-Wyck.

CONCLUSION AND DISCUSSION

The main thrust of the present paper has been to illustrate the construction and application of conjoint-based choice simulators to predict the effects of retail change on consumer choice behaviour and turnover levels in a dynamic framework. The findings of the present study generally support the approach. The validity of the conjoint measurement is good; the predictive validity of the choice simulator is also satisfactory and, finally, planned retail change can be easily accommodated in the approach.

The approach clearly has some advantages over the more traditional gravity models. The approach is explicitly based on measurements of consumer decision-making and preference. The parameters of the model are not influenced by the geometry of the study area. Consumer information fields are included in the model and, finally, an attempt is made to incorporate retailers' reactive behaviour.

Nevertheless the approach may be improved in different respects. First, rather than adopting an aggregate model to predict individuals choice sets, an individuals-level approach may be attempted, or, alternatively, individuals choice sets may be generated from the aggregate probabilities, using Monte Carlo simulation techniques. Second, more influential attributes of shopping centres may be included in the analysis. Third, the submodel of retailers' reactive behaviour might be advanced and extended to a set of behaviour types that also includes more general responses. The authors hope to report about such developments in the near future.

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