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Choice Experiments versus Revealed Choice Models: A Before-After Study of Consumer Spatial Shopping Behavior

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The purpose of this article is to compare a set of multinomial logit models derived from revealed choice data and a decompositional choice model derived from experimental data in terms of predictive success in the context of consumer spatial shopping behavior. Data on consumer shopping choice behavior as collected before the opening of a new major clothing store in a shopping center were used to estimate the parameters of the various models. The estimated parameters were then used to predict market shares of the shopping centers after the opening of the new store. Predicted shares were then compared with data on actual behavior collected after the opening of the new store. Results indicate that the two modelling approaches perform almost equally well. **Key Words: revealed choice models, decompositional choice models, consumer behavior, prediction.**

Introduction

Over the last three decades spatial interaction and spatial choice models of varying degrees of sophistication have been employed widely by both academics and practitioners to describe consumer shopping behavior and predict the likely impact of (planned) retail change on such behavior. Models of consumer spatial shopping behavior have been used for determining the optimal location of new stores or shopping centers, predicting market shares of new stores or centers, determining the optimal size of a new store at a given location, and examining the likely impacts, in terms of market shares or sales volumes, of retail planning proposals on existing shopping centers (e.g., Davies 1974; Fotheringham 1988).

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Two different modelling approaches have dominated this field of study: revealed choice models and decompositional preference/choice models. Although these approaches have much in common from a theoretical perspective, they differ fundamentally in terms of methodology and data requirements. Revealed choice models derive their parameters from data on observed consumer choice behavior in real-world settings. Respondents are typically asked which real-world centers they usually patronize for shopping. The parameters of the model are then estimated by relating these data on observed consumer choices to a set of shopping center attributes which is assumed to influence consumer choice behavior.

In contrast, decompositional preference and choice models are not derived from data on consumers' actual choices, but from consumer preferences or choice for hypothetical shopping centers described in terms of a set of attributes. This approach typically involves specifying, testing, and applying choice models based on data obtained in preference or choice experiments. Individual responses to hypothetical choice alternatives are used for estimating preference or utility functions. These hypothetical shopping centers, or, alternatively, existing shopping centers with modified attributes are constructed according to the principles of the design of statistical experiments.

There is a rich literature on the pros and cons of these two modelling approaches (e.g., Golledge and Timmermans 1988; Wrigley 1988). We will not discuss this at any length. To understand the significance of the present paper, it is important though to stress the difference between the two modelling approaches in terms of prediction. Revealed choice models only allow one to simulate the impact of retail planning proposals indirectly. Because these models use actual attributes of shopping centers as explanatory variables, the impact of planning proposals can only be assessed by defining planning proposals in terms of these explanatory variables of the model. The impact of retail planning proposals on consumer spatial shopping behavior can then be predicted by using the adjusted values of the explanatory variables, and by assuming that the estimated parameters are invariant across time. Thus, revealed choice models can be used for prediction if one is willing to assume that the estimated model can be generalized to the new choice situation. In contrast, the experimentally based decompositional preference and choice models allow one to design controlled experiments in which choices under different retail planning scenarios can be observed directly (Louviere 1984). Consequently, models relating retail planning proposals directly to consumer choice can be estimated by assuming that consumer choice behavior under experimental conditions generalizes to the real world.

Unfortunately, to the authors' knowledge, the predictive success of these two different modelling approaches has never been the subject of empirical investigation in a before-after study of consumer spatial shopping behavior. The aim of the present study, therefore, is to fill this gap by comparing an experimentally based choice model to a set of revealed choice models in terms of predictive validity.

The article is organized as follows. First, we outline some of the theory underlying the two modelling approaches. Second, we describe the study area and the data. The third section presents the results of the estimation of the various models and compares their predictive success. The final section discusses some issues for future research.

The Models

Revealed Choice Models

Although the term revealed choice model refers to many different types of models, interest in the present study was restricted to the multinomial logit model (MNL) because it is best known and most frequently applied in studies of spatial shopping behavior (Koppelman and Hauser 1978; Landau et al. 1982; Gautschi 1981). The multinomial logit model assumes that the probability of an individual located at place i choosing shopping center j out of J shopping centers can be represented by the following equation:

$$P_{ij} = \exp(V_j) / \sum_{j'} \exp(V_{j'}) \qquad (1)$$

where V_j represents the deterministic part of the utility an individual receives from choosing shopping center j. The utility term may take on different functional forms, but most commonly a linear additive function of shopping center attributes ($\mathbf{X}_{jk}$) is assumed. Hence,

$$V_j = \beta_k \mathbf{X}_{jk} \quad (2)$$

From a theoretical viewpoint, the multinomial logit model can be derived from Luce's choice theory or Lancaster's consumption theory. It has interpretations both in terms of strict and random utility theory. Interested readers are referred to Hensher and Johnson (1981) and Ben-Akiva and Lerman (1985) for details on the theoretical underpinnings of this model.

In an applied retail planning context, different operationalizations of the X-terms in equation (2) may be used. Three different specifications were tested in the present study. First, consumer shopping choice behavior was assumed to be a function of a set of objective, physical attributes of the shopping centers. Second, rather than using physical attributes, consumer evaluations of these attributes were used as the explanatory variables of the model. Third, because evaluations are difficult to use in prediction, a model which relates attribute evaluations to their objective values in a separate modelling step was tested.

Most applied multinomial logit shopping models involve a generic utility function. Consequently, researchers assume that the effects of the selected attributes do not vary between shopping centers. In contrast, the decompositional choice model used in this study involves alternative-specific utility functions. Consequently, one could argue that the two modelling approaches are difficult to compare because they are based on a different number of parameters. Of course, this argument is true from a statistical viewpoint; on the other hand, the comparison of different modelling approaches as they are typically used in applied contexts is an important research issue as well. Therefore, we decided wherever possible to estimate the revealed choice models with and without alternative-specific constants.

Choice Experiments

To better understand decompositional choice models, it is important to summarize the specific methodological principles associated with this approach that have received only limited application in retail geography and planning. Decompositional models were developed in response to the aggregate spatial interaction models of the 1960s. There was some belief that these "econometric" models may obscure true utilities because the estimated utility function is typically dependent upon limited variances in observed explanatory variables, and because of the existence of ecological correlations and near-multicollinearity. These problems are typical of revealed choice data because the researcher cannot control the properties of the data.

In contrast, the decompositional approach does allow one to control the properties of the data by designing experiments. This modelling approach is based on the assumption that individuals' choice behavior is the result of a decision-making process in which they integrate their evaluations of attributes of choice alternatives. According to some simple combination rule or utility function, consumers are assumed to make value judgements about attribute levels (e.g., selection, price, parking) and combine these into an overall judgement of choice alternatives (e.g., shopping centers). Given these overall judgements, consumers are assumed to decide which alternative, if any, to choose from their choice set.

Decompositional models have these assumptions in common with revealed MNL models but differ in terms of data requirements. The form of the utility function is typically tested by designing an appropriate experiment and performing statistical or axiomatic analyses on the responses (for more details see Bates 1988; Louviere 1988; Moore 1985, 1988; Timmermans 1984). Choice experiments are an alternative to the better known preference experiments that have been applied frequently in studies of spatial shopping behavior (Moore 1988; Schuler 1979; Timmermans 1980, 1982; Timmermans et al. 1984; van der Heijden and Timmermans 1988).

The construction of a decompositional choice model involves the following steps/decisions. First, one identifies the attributes considered relevant to the choice process of interest. These attributes are then described in terms of attribute levels. Next, the attribute levels are combined to generate profiles of hypothetical alternatives. The attribute profiles may be generic, but, alternatively, the profiles may describe named choice alternatives, such as real world shopping centers. Profiles are usually obtained from full factorial or fractional factorial designs. Full factorial designs involve all possible combinations of attribute levels and allow one to estimate all main and all interaction effects. A fractional design involves only a fraction of the full factorial design and hence allows one to estimate only some effects. Fractional designs thus assume that all higher order interaction effects are negligible and hence can be ignored. The simplest designs are the main effects plans which permit one to estimate only the main effects, implying that one assumes the additive model to be appropriate. If one wishes to estimate a multilinear model, an appropriate fractional factorial design which allows the estimation of all main effects plus the selected interaction effects of interest should be constructed.

Choice designs require the additional step that the hypothetical choice alternatives or profiles are placed into choice sets. This should be done such that the assumptions of the assumed choice model are satisfied. For example, fractional factorial designs satisfy the assumptions underlying the MNL model. 2^n designs can be used to place N named choice alternatives or profiles into choice sets of different size and composition. Thus, a two-level variable (present or absent) is used to create choice sets of different size and composition. Alternatively, one can fix the number of alternatives in each choice set but vary the attributes that describe the choice alternatives (Louviere and Woodworth 1983). For example, if one has three shopping centers described by two, three, and four three-level attributes respectively, one could construct an orthogonal fraction of the resulting 3^9 full factorial design to create choice sets. Each set would consist of the three shopping centers, but the attribute profiles of the shopping centers would vary across choice sets. A third possibility, the one adopted in this study, is to first develop fractional factorial designs for each named shopping alternative separately, and then combine randomly profiles of the various shopping centers. In principle, this randomization procedure should render the marginals of the shopping centers independent of each other, or at least keep correlations between them low. More details on design strategies can be found in Louviere (1988) and Louviere and Timmermans (1990b).

Once the choice sets are constructed, subjects are asked to choose a single center from each choice set or, alternatively, to allocate some fixed number of resources (trips, money, etc.) among the alternatives in each choice set. Because the dependent variable of the model now represents choice frequencies, OLS multiple regression analysis, which is typically used for preference design data, is not an appropriate technique. To analyze the choice data, one should use alternative techniques such as logit regression analysis (Theil 1969), weighted least squares involving a log transformation of the data (Nakanishi and Cooper 1974), or iteratively reweighted least squares (Woodworth and Louviere 1985). The interested reader is referred to Louviere and Timmermans (1990a) for further details about these estimation techniques.

Study Area and Methods

The two major municipalities in the Eindhoven region of The Netherlands are Eindhoven and Veldhoven. Both municipalities have developed retail planning proposals to improve the attractiveness of their main shopping centers. At the time of this study, Eindhoven was considering the construction of a new in-town shopping complex on a former hospital site. The plan was to develop this shopping complex jointly with a new music hall and abundant parking spaces in an underground parking facility. The municipal council of Veldhoven had just approved the opening of a new major clothing store on a former library site. The municipality was also developing plans for improving the accessibility of its main shopping center. The question underlying the present research project was how these retail planning actions of competing shopping centers would affect consumer spatial shopping behavior in a specific neighborhood of Veldhoven.

The analyses presented in this article are based on data that were gathered before and after the opening of the new clothing store in March and September 1988, respectively. The store opened in April 1988. A random sample of 110 households was drawn for the "before" study. Data on their shopping choices were used to estimate the various choice models. The "after-sample" consisted of 149 respondents. The predictive ability of the various models was tested against these data. In both samples, the member of the household responsible for shopping was asked to complete the questionnaire. Respondents were asked how often they visited the shopping centers which were familiar to them. They were also requested to express their degree of satisfaction with parking, selection, and travel time for each of these centers. Finally, they were asked to respond to the choice experiment.

Previous research has indicated that the majority of the residents of the neighborhood of interest patronized four shopping centers: Veldhoven city center; Eindhoven city center; Veldhoven-Burgemeester van Hoofflaan, a neighborhood center in Veldhoven; and de Hurk, Eindhoven, a peripheral discount-type shopping center. A set of possible planning actions was developed for each of these four shopping centers. The actions for Veldhoven city center were the opening of a new major clothing store (Marca), an increase in the total floorspace of 10%, and a 10% extension of the number of parking spaces. Possible actions for Eindhoven city center were a new major in-town hypermarket located close to the market square, a 15% increase of parking costs, 600 additional underground parking spaces, and a 10% increase in the total floorspace for shops. All these actions were actually under consideration by the respective planning authorities and could be implemented or not.

The actions considered for de Hurk shopping center were the opening of an additional major food store and a 5% increase in the number of parking spaces. Possible actions for the Burgemeester van Hoofflaan shopping area consisted of a diversification of types of shops, the realization of a pedestrianized shopping street, and the opening of a major appliance store. These actions were all hypothetical.

Each action was treated as a two-level factor (implement or not). Because the number of actions differs between shopping centers, either a full or a fractional factorial design was constructed for each shopping center separately to represent different combinations of actions. The full factorial design was used for those centers with two or three actions, and it involves $2^2 = 4$ and $2^3 = 8$ scenarios, respectively. Similarly, the full factorial for Eindhoven city center would consist of $2^4 = 16$ scenarios, but in this case, only a 1/2 orthogonal fraction was used. Eight choice sets were constructed by assigning at random without replacement specific scenarios for each shopping center. The four designs consisting of four scenarios only were used twice to construct the eight choice sets. A base alternative ("any other shopping center") was added to each choice set for estimation reasons. The choice of the base alternative indicates a loss of market share of the shopping centers of prime interest. Choice sets were randomized across respondents and respondents were asked to allocate their monthly shopping trips among the four shopping centers and the base alternative included in each choice set.

Unfortunately, the revealed choice models cannot be based on exactly the same set of attributes. However, an attempt was made to select a set of explanatory variables that would relate to the same underlying concepts. In particular, the following physical attributes of the shopping centers were used as explanatory variables: presence of pedestrianized area, number of parking spaces, square meters of floorspace for appliances and clothing, number of appliance and clothing stores, total floorspace, total number of shops, total number of functional units, paid versus free parking, and distance in kilometers. Some of these attributes are strongly correlated and, as we will see later, only a few of these attributes were included in the final revealed choice model.

Analysis and Results

The following analyses were conducted. First, the parameters of the various choice models were estimated using the "before-data." These estimated parameter values were then used to predict consumer choice behavior after the opening of the Marca store. Finally, predicted market shares of the shopping centers were compared with observed shares using the "after-data."

Estimation

Logit Models Based upon Revealed Choices. We first discuss the estimation results obtained for the multinomial logit model with physical attributes. The parameters of this model were estimated using iteratively reweighted least squares analysis. Table 1 shows that the parameters all are in the anticipated directions. The probability of choos-

Table 1 *Parameters of the Multinomial Logit Models with Physical Attributes*

(a) Without Alternative-Specific Constants

Physical Attributes	Parameters	Standard Error	T-value
Distance	−0.6177	0.009	−72.047
Pedestrianized shopping area	0.1690	0.016	10.635
Floorspace for clothing (sq. meters)	0.5047	0.018	27.510
Total number of functional units	0.0063	0.001	5.585
Goodness-of-fit Measures	**Flows**	**Turnover**	
Correlation coefficient	0.725	0.999	
Robinson's agreement measure	0.847	0.999	
Standardized root mean square	0.782	0.038	
Standardized mean absolute error	0.528	0.034	
Mean percentage error	119.538	19.499	

(b) With Alternative-Specific Constants

Alternatives and Physical Attributes	Parameters	Standard Error	T-value
Veldhoven city center	−0.2981	0.020	−14.800
Eindhoven city center	−1.6155	0.065	−24.986
Veldhoven Burgemeester van Hoofflaan	0.7132	0.015	48.539
Eindhoven de Hurk	−1.4338	0.052	−27.802
Distance	−0.4114	0.015	−26.893
Pedestrianized shopping area	0.9624	0.010	97.072
Floorspace for clothing (sq. meters)	0.5329	0.003	187.953
Total number of functional units	0.0081	0.003	2.737
Goodness-of-fit Measures	**Flows**	**Turnover**	
Correlation coefficient	0.729	1.000	
Robinson's agreement measure	0.851	1.000	
Standardized root mean square	0.777	0.011	
Standardized mean absolute error	0.521	0.008	
Mean percentage error	109.783	0.840	

ing a shopping center increases if the shopping area is pedestrianized. Choice probabilities also increase with increasing floorspace for clothing and an increasing number of functional units. As expected, consumers are less likely to patronize shopping centers with increasing distance. Although all parameters are significant beyond conventional levels, the distance and floorspace variables are the most important variables influencing consumer shopping center choice.

This model based on physical attributes is capable of reproducing observed shopping choices very well as indicated by the values of the selected goodness-of-fit measures. To interpret these measures correctly, one should realize that the correlation coefficient expresses only the strength of a linear relationship between predicted and observed choice frequencies. The problem with the correlation coefficient is that it does not necessarily indicate departures from the $x = y$ regression line. Therefore, Robinson's agreement measure (Robinson 1957, 1959) which explicitly measures departures from the $x = y$ line, was calculated as well. This measure is based on quadratic departures from the averages for each pair of data values, and consequently, it weighs larger departures more heavily than smaller departures and is not influenced by the scale of the data. The mean percentage error has a direct interpretation, but one should realize that small absolute prediction errors might result in large percentage errors for low choice frequencies and therefore might also result in high mean percentage errors. Keeping this in mind, the model predicts turnover almost perfectly; the mean percentage error is only 19.5% and the correlation coefficient and Robinson's agreement measure indicate a strong fit. As usual, the goodness-of-fit measures obtained for the flows (zone-specific choice frequencies) are smaller. The model with alternative-specific constants produces better results in predicting turnover (total number of consumers visiting a shopping center), which is not surprising because it has more parameters.

The second version of the multinomial logit model uses average evaluations as explanatory variables. The estimated parameters of this model and its goodness-of-fit measures are presented in Table 2. The only parameter that is statistically significant beyond the .05 level is the distance variable. The estimates indicate that the evaluation of shopping center attributes improves with more parking facilities, greater selection, and a larger number of appliance stores, whereas it decreases with increasing distance from the residence to the shopping center. Similar effects are obtained for the alternative-specific model.

The model based on average attribute evaluations performs only slightly weaker than the model based on physical attributes, a finding which might suggest that consumer evaluations of shopping center attributes are monotonically related to actual attribute levels. The second model's ability to predict the pattern of consumer shopping trips is highly similar to the results obtained for the first model. Its

Table 2 *Parameters of the Multinomial Logit Models with Average Evaluations*

(a) Without Alternative-Specific Constants

Variables Evaluated	Parameters	Standard Error	T-value
Distance	−0.1561	0.003	−48.8480
Parking	0.0007	0.001	0.6320
Overall selection	0.0022	0.001	1.6560
Number of appliance stores	0.0007	0.001	0.9310
Goodness-of-fit Measures	Flows	Turnover	
Correlation coefficient	0.723	0.998	
Robinson's agreement measure	0.845	0.999	
Standardized root mean square	0.704	0.057	
Standardized mean absolute error	0.501	0.053	
Mean percentage error	134.895	42.271	

(b) With Alternative-Specific Constants

Alternatives and Variables Evaluated	Parameters	Standard Error	T-value
Veldhoven city center	0.0060	0.038	0.160
Eindhoven city center	0.6994	0.092	7.630
Veldhoven Burgemeester van Hoofflaan	0.2997	0.071	−8.613
Eindhoven de Hurk	−0.8437	0.035	−11.952
Distance	−0.1762	0.008	−23.273
Parking	0.0007	0.001	0.777
Overall selection	0.0022	0.001	1.795
Number of appliance stores	0.0046	0.000	13.278
Goodness-of-fit Measures	Flows	Turnover	
Correlation coefficient	0.727	1.000	
Robinson's agreement measure	0.848	1.000	
Standardized root mean square	0.699	0.000	
Standardized mean absolute error	0.491	0.000	
Mean percentage error	128.050	0.075	

success in predicting turnover at the shopping center level however is slightly less. The results obtained for the alternative-specific model illustrate that the inclusion of alternative-specific constants does not significantly affect the ability to predict shopping flows. However, the inclusion of these constants does improve the prediction of turnover.

Models based on evaluations are difficult to apply to real-world retail planning problems because it is not readily evident how planning proposals will affect consumer evaluations. In order to assess the likely impact of such proposals, one must estimate separate submodels describing the relationship between consumer evaluations and physical, manipulable attribute levels of shopping centers. Therefore, the third model links average attribute evaluations to physical attributes in a separate modelling step. More specifically, the relationship between the evaluation of parking, available appliance stores, and selection and their physical counterparts was estimated. These variables were selected because they are commonly used in applied research projects on consumer shopping choice behavior in The Netherlands. The consumer's estimate of travel time was related to actual distance in kilometers by the following equation:

$$d^*_{ij} = 6.5934 + 1.0873\, d_{ij} \tag{3}$$

where d^*_{ij} is the travel time to the jth shopping center from residential zone i; and d_{ij} is the physical distance between i and j. The Pearson product moment correlation coefficient between observed and predicted observations was 0.883.

Equation (4) represents the relationship between the average evaluation of parking and two parking variables. It was assumed that parking could be described by the number of parking spaces, categorized in terms of three attribute levels, 0-250, 251-1,500 and 1,501-5,000 spaces, and paid versus free parking. Effect coding was used to represent the number of parking spaces. The Pearson product moment correlation coefficient between the observed and predicted evaluation was 0.561. The mean percentage error was only 16%, which was less than the mean percentage error obtained for distance (36%).

$$p^*_j = 60.7712 - 4.4363\, X_{1j} + 3.6025\, X_{2j} - 7.3775\, X_{3j} \tag{4}$$

where p^*_j is the evaluation of parking for shopping center j; X_{1j} is 0-250 parking spaces; X_{2j} is 251-1,500 parking spaces; and X_{3j} is paid parking. Equation (4) indicates that consumers have the tendency to prefer medium-sized parking lots, and also that they evaluate free parking as better than paid parking.

The evaluation of available appliance stores was related to floorspace in squared meters for appliances and the square of the number of appliance stores in the shopping center. The squared term appears in the equation to account for nonlinearities in the observed evaluation scores. The estimated equation can be represented as

$$a^*_j = 63.5844 + 0.3868\, (X_{1j}/1000.0) + 0.0257\, X^2_{2j} \tag{5}$$

where a^*_j is the evaluation of available appliance stores in shopping center j; X_{1j} is the floorspace in square meters in shopping center j; and X_{2j} is the number of appliance stores in shopping center j.

The equation indicates that the evaluation of available appliance stores increases with increasing floorspace and selection. The correlation between predicted and observed evaluations was 0.468; the mean percentage error was 10%.

Finally, it was assumed that total floorspace in squared meters and total number of functional units would influence people's evaluation of the selection variable. The estimated equation is

$$s^*_j = 24.6068 + 0.1120\,(X_{1j}/1000.0) + 1.3743\,X_{2j} \quad (6)$$

where s^*_j is the evaluation of the selection variable for shopping center j; X_{1j} is total floorspace in square meters in shopping center j; and X_{2j} is the number of functional units in shopping center j. Equation (6) suggests that indeed the evaluation of available selection is systematically related to corresponding objective measures. The correlation coefficient is 0.783, and the mean percentage error is 28%.

Having estimated these submodels, the predicted evaluation and the estimated parameters of Table 2 can be used to predict observed consumer shopping behavior patterns (Table 3). The results are as anticipated. Because one now has separate submodels relating physical attributes to consumer evaluations and a submodel linking consumer evaluations to actual shopping choice behavior, the predictive success of this combined model is less than the predictive success of the previous two models. The model with alternative-specific constants does not perform better than the generic model. This result seems to suggest that the alternative-specific constants cannot compensate for the errors made in the submodels in relating physical attributes to consumer evaluations.

Table 3 *Goodness-of-fit of the Multinomial Logit Models with Evaluation/Physical Attribute Submodels*

(a) Without Alternative-Specific Constants

Goodness-of-fit Measures	Flows	Turnover
Correlation coefficient	0.679	0.991
Robinson's agreement measure	0.797	0.976
Standardized root mean square	0.753	0.229
Standardized mean absolute error	0.574	0.217
Mean percentage error	273.394	103.303

(b) With Alternative-Specific Constants

Goodness-of-fit Measures	Flows	Turnover
Correlation coefficient	0.674	0.958
Robinson's agreement measure	0.795	0.962
Standardized root mean square	0.757	0.290
Standardized mean absolute error	0.582	0.213
Mean percentage error	300.979	70.518

Choice Model Derived from Experimental Design Data. The choices observed in the experiment were aggregated for each choice set separately across respondents. This produces $8 \times 5 = 40$ frequency observations. Iteratively reweighted least squares analysis was used to estimate the parameters of a multinomial logit model. The dependent variable consists of the choice frequencies whereas the independent variables consist of a series of indicator variables used for coding the attribute vectors; i.e., the specific effects of each shopping center are captured by dummy variables. If an observation pertains to a particular shopping center, it is coded as one and as zero otherwise. Effect coding (1, −1) was used to code the retail planning proposals and choice sets were represented by set-identifiers.

All parameters in the model (Table 4) are statistically significant beyond the 5% level except those associated with an increase of the floorspace in Veldhoven city center, an increase in floorspace in Eindhoven city center, and the realization of a pedestrianized shopping street in the Burgemeester van Hoofflaan center. All parameters have the expected sign except those pertaining to the location of a new hypermarket in Eindhoven city center. However, this proposal appears to have only a minor effect on consumer spatial choice behavior. The results suggest that the utility of the Veldhoven city center shopping center is most affected by the opening of the Marca clothing shop, followed by the 10% additional parking spaces. The proposal that would most increase the utility of the Eindhoven city center is the creation of 600 additional parking spaces. The envisaged planning actions for the de Hurk center appear to have an almost equal effect in the utility of this center, whereas the findings suggest that a diversification policy would

Table 4 *Parameters for the Experimentally Based Choice Model*

Variables	Coefficient	Standard Error	T-value
Veldhoven City Center	1.211	0.006	189.51
Location of Marca clothing store	0.033	0.004	7.61
10% increase of total floorspace	0.003	0.004	0.72
10% increase of parking spaces	0.011	0.005	2.43
Eindhoven City Center	−1.013	0.011	−93.21
Location in-town hypermarket	−0.019	0.010	−1.96
15% increase in parking costs	−0.033	0.010	−3.38
600 additional parking spaces	0.040	0.010	4.16
10% increase of total floorspace	0.001	0.010	0.08
De Hurk Center	−2.109	0.017	−123.55
Location of major food store	0.075	0.016	4.59
5% increase of parking spaces	0.063	0.017	3.81
Burgemeester van Hoofflaan Center	1.141	0.006	225.12
Diversification of types of shops	0.151	0.004	35.16
Pedestrianized shopping street	0.006	0.005	1.42
Location of major appliance store	0.021	0.004	5.13

have the largest impact in the utility of Burgemeester van Hoofflaan shopping center.

Prediction

Evidence of the predictive validity of the choice models can be obtained by using the estimated parameters described above to predict the impact of the opening of the Marca store and by comparing these predictions with actual data on consumer shopping choice behavior derived from the after-sample. Table 5 presents the results obtained for the various models. A number of conclusions may be drawn from the results. First, most models satisfactorily predict actual consumer shopping choice behavior after the opening of the new store, compared to the results reported elsewhere in the literature. Second, the predictive success of the choice models with alternative-specific constants is always higher than the predictive success of the generic models. Third, three out of five goodness-of-fit measures indicate that the logit model with physical attributes based on revealed choices is outperformed by the model based on average evaluations and the model which combines average evaluations and physical attributes. This finding is consistent with claims in the literature that one needs to take consumers' evaluations and preferences into consideration to understand their actual choice behavior. Revealed choice models that are derived from physical attributes only do not say much about consumer preferences; these models are statistical, correlation-based models. They may produce satisfactory predictions from an applied viewpoint as long as the functional relationships upon which these models are based remain more or less constant across time; otherwise, these models are bound to fail in terms of predictive success. Finally, the predictive ability of the decompositional choice model is almost as good as that obtained for the first two models derived from revealed choices. If one insists on using mean percentage error as an indication of predictive success, the decompositional model clearly outperforms all other choice models in the present study.

Conclusion and Discussion

The aim of this study has been to compare the predictive performance of a series of consumer spatial shopping models. In addition, the present study sheds some light on the potential use of choice experiments for predicting the consequences of retail planning actions on consumer spatial choice behavior. Before drawing some conclusions, it should be emphasized that comparing the predictive performance of different modelling approaches is always very difficult in that one can always argue that the researchers have not been completely fair to one of the models. Strictly speaking, model comparisons are optimal only if the various models are hierarchical. However, models belonging to different model classes can never be hierarchical. In the present study, we have tried to keep attributes as similar as possible, and use similar specifications. Both types of models may produce better predictions if other specifications or operationalizations are adopted. We should also realize that the models have been compared using only one data set which obviously may contain measurement errors. Hence, it is not difficult to criticize the present study from a statistical point of view. However, from an applied retail planning point of view, one is primarily interested in the overall performance of the model. Also, we have tried to specify

Table 5 *Predictive Success of the Choice Models*

Models	Goodness-of-fit Measures				
	Correlation Coefficient	Robinson's Agreement Measure	Standardized Root Mean Square	Standardized Mean Error	Mean Percent Error
Revealed choice data:					
MNL/Physical Attributes					
Without alternative specific constants	.974	.985	.152	.151	30.387
With alternative specific constants	.983	.989	.131	.129	28.350
MNL/Evaluations					
Without alternative specific constants	.967	.983	.155	.128	31.77
With alternative specific constants	.978	.989	.127	.104	28.22
MNL/Physical Attributes + Evaluation					
Without alternative specific constants	.944	.972	.196	.160	29.03
With alternative specific constants	.970	.984	.144	.114	20.23
MNL/Experimental Design Data	.985	.988	.139	.113	12.77

the various shopping choice models as they are typically used in retail planning.

The results of this study suggest that the decompositional choice model performs equally well as the revealed choice models that include alternative specific constants. The former clearly outperforms the generic versions of the logit models derived from revealed choices, the latter being commonly used in an applied retail planning context. If these results can be generalized, the present study suggests practitioners need not be greatly concerned about presumed differences in predictive ability between these two modelling approaches. The choice of model should be dictated by cost considerations, amount and kind of information required, and other similar considerations. Choice experiments are less costly in that sample sizes that are typically required to estimate choice models for a given confidence level are smaller. However, choice experiments do need specialized advanced knowledge and, if done properly, considerable care and preparation. If the experiments are designed properly and if respondents are well introduced to their experimental task, choice experiments are no more difficult to implement than the better known preference experiments. On the other hand, surveys from which revealed logit models are derived are probably more appropriate if a wide variety of detailed information is required. ■

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