

A CONJOINT MEASUREMENT MODEL OF CONSUMER SPATIAL BEHAVIOR

Harry J. Schuler and David C. Prospero*

This study reports a strategy to measure and assess the relative importance of specific attributes in establishing space preference functions for supermarkets. Conjoint measurement is used to estimate numerical parameters for experimental levels of supermarket attributes which accurately describe the manifest order relations in the choice data. The model of spatial choice is consistent with existing theories of consumer behavior.

Traditionally, economic analyses emphasized utility maximizing hypotheses or probabilistic hypotheses to explain how people choose among complex decision alternatives. Cesario and Smith [6, p. 57] comment that, ". . . these two approaches can be viewed as constituting opposite extremes within a spectrum of possible hypotheses" or viewed in another way, ". . . the utility maximizing hypotheses presume that spatial interaction decisions are highly structured. . . whereas the probabilistic hypotheses presume just the reverse." Given that this is the case, there is an important range of decision rules between the extremes which require more specific behavioral treatment.

Increasingly, research efforts in decision theory are adopting models of choice-making based on Lancaster's [13] formulation of consumer behavior. The object of consumer utility for commodity bundles was modified to include the notion that utility for goods should be evaluated in terms of preferences for attributes assumed to underlie the goods. In economic terms, utility is derived from the attributes that goods are cognized to possess and not directly from the goods themselves. These want-satisfying attributes may be either physical qualities associated with the goods or subjectively defined criteria.

The ability to explore the multiattribute choice problem in more depth than was previously possible is a direct result of contributions from mathematical psychology and psychometrics. This is evident, for example, in the recent development of operational models and scaling procedures for portraying choices among complex decision alternatives [1, 7, 11, 22]. The

*Doctoral students, Department of Geography, Indiana University at Bloomington. The authors would like to thank David B. MacKay and John Odland of the Department of Geography at Indiana University for their comments on an earlier draft.

objective is to analyze the joint effects of many attributes by specifying an appropriate combination rule.

Two types of information processing models can be distinguished: composition and decomposition models. Composition models derive a vector of utilities by combining measures of independent attributes exogenously determined. This class of models is appropriate when measurements of independent attributes are known and possess the properties of interval or ratio scale data. In such cases, it is possible to combine attributes so that overall utility values for alternatives can be determined. Operational forms of composition models in the field of consumer behavior include the abstract mode model [19], functional measurement procedures [15], and additive weight models [5].

The decomposition models are usually associated with multidimensional scaling (MDS) and conjoint measurement techniques. These models begin with information collected experimentally and then reduce the complex data into subsets each identifying distinct component parts. The usefulness of scaling procedures in cognitive research lies partly in their ability to transform judgments made on the basis of ordinal ratings such as "I prefer A to B," into interval or ratio scale measurements of the underlying components of the decision process. A major critique of MDS models in the analysis of choice data is that the underlying components may be difficult to interpret [3, 4, 16]; a problem common to data reduction methods.

In contrast to multidimensional scaling techniques conjoint measurement methods have received little discussion and application in the economics and geography literature. The major distinction between MDS and conjoint measurement is that in the latter individuals explicitly evaluate multi-attribute alternatives composed of experimental levels of attributes which are known but cannot be measured independently. In this case it is desirable to, simultaneously, reduce the complex phenomenon to its basic attributes and, to obtain a measurement of these attributes such that the combination of attributes accounts for the order of the observation [9]. The decomposition of ordinal ranked multiattribute alternatives into preference functions is the conjoint measurement problem; the combination rule is called the conjoint measurement model [14, 23, 24].

Conjoint Measurement

The general conjoint measurement model is based on the premise that choice behavior is governed by a decision rule that may be revealed by ranking alternative stimuli having attributes varied in systematic ways [10]. This formulation is analogous to the revealed preference approach for identifying preference structures [20, 21]. Measurement values indicate the trade-offs associated with a set of attributes, and appear to have the basic properties of utilities [3].

THE MODEL

Consider the multiattribute choice problem in terms of m attributes ($m \geq 2$). Let X denote the combination of $X_1, X_2, \dots, X_j, \dots, X_m$ where X_j represents the set of states of attribute j . A particular alternative j is described as an ordered m -tuple:

$$(1) \quad x = (x_1, x_2, \dots, x_j, \dots, x_m)$$

where x_j is the level of alternative x of the j th attribute. From classical theory of consumer behavior, it can be asserted that:

$$(2) \quad U(x) \geq U(x') \iff x \succeq_0 x'$$

where $U(x)$ denotes the utility of x and \succeq_0 denotes "is preferred to," that is, \succeq_0 represents an observable or empirical relationship.

Given that only the order and composition of x, x', \dots, x^n are known (i.e., $x = (x_1, x_2, \dots, x_m)$; $x' = (x'_1, x'_2, \dots, x'_m)$; \dots ; $x^n = (x^n_1, x^n_2, \dots, x^n_m)$) a transformation is sought whose values $U(x), U(x'), \dots, U(x^n)$ are monotonically related to the order of the original observations. The monotonic transformation is carried out by specifying a combination rule which describes how the attributes are to be joined in deriving the values of $U(x_i)$.

The model is fit iteratively, by a process that seeks to minimize stress. A configuration of points whose ranks of interpoint distances best preserves the orderings of the original observations is determined. Stress is defined by the expression:

$$(3) \quad s = \left[\frac{\sum_{i=j}^n (d_{ij} - \hat{d}_{ij})^2}{\sum_{i=j}^n (d_{ij} - \bar{d})^2} \right]^{1/2}$$

where

d_{ij} denotes the interpoint distance between the (ij) th pair of points;

\hat{d}_{ij} denotes a set of derived values, chosen to be as close to the d_{ij} as possible, subject to being monotone with the original rankings; and

\bar{d} denotes the mean of the d_{ij} [9].

If a perfect least-squares solution is possible \hat{d}_{ij} will equal d_{ij} in all cases and a perfect recovery of original rankings will occur.

Problem

A conjoint analysis of consumer preference for supermarket attributes is carried out. Results are utilized in two ways: (1) to test the adequacy of the combination rule in accounting for observed orderings; and (2) to identify collective preference functions for two distinct client groups by examining attribute scales.

The adequacy of the combination rule is usually evaluated by measures of stress. If stress measures are deemed acceptable the combination rule can be adopted as a useful model of decision making. However, stress is only useful for determining goodness-of-fit between the original observations and a final configuration of points in n-dimensional space and is not testable statistically. As such, it is a measure of the internal consistency of a respondent in ordering multiattribute alternatives.

Consequently, another approach is utilized here. The concept of multi-operationism is invoked to validate the combination rule [2]. This is accomplished by comparing derived and stated preference orderings for eight supermarkets in a specific space economy. The rationale for this approach is outlined in Brummell and Harman [2] and is becoming a standard procedure for verification in both the psychology and geography literature [15, 17].

Derived preference orderings are obtained by substituting attribute scale weights from an experimental situation for ordinal attribute ratings of supermarkets. The transferral of scale weights is justified if both tasks -- ranking of hypothetical grocery alternatives and rating actual supermarkets -- are preference activities [2]. Overall utility is then determined for each supermarket on an individual basis. A preference ordering is established by averaging derived values across individuals and then ordering supermarkets. The stated preference ordering for the same outlets is computed accordingly from another set of data. The two rankings are expected to be positively correlated.

While behavioralists emphasize the need to collect data at the individual level, analysis and results are often presented in aggregated form. The significance of this approach lies in a desire to contribute to the understanding of large scale pattern and process. In this paper, collective preference functions are examined for two groups of shoppers, identified on the basis of patronage patterns. Members of the first group are customers at four urban supermarkets in commercial districts; the second group consists of shoppers at four suburban supermarkets in predominantly residential areas. If cognition of these outlets vary only slightly from consumer to consumer then differences in patronage between the two groups are related in part to dissimilar preferences for attributes.

Data

Data were collected in 1974 from 78 consumers in Bloomington, Indiana,

during a two-stage interview.¹ In the first stage, shoppers were randomly selected at each of eight local supermarkets and questioned about their familiarity with the other seven supermarkets. Familiarity was described as having knowledge about grocery shopping alternatives. If the respondent was familiar with the eight supermarkets, arrangements were made for a second interview. During the subsequent session four sets of detailed information were collected: the subject's rank-ordered preference for the local supermarkets; ratings of the eight supermarkets over the attributes price of merchandise, relative size, and traveling distance; a rank-ordering of 25 hypothetical grocery alternatives defined over the same attributes; and the subject's shopping pattern.

The first set of data contains each subject's ranking of eight local supermarkets from "most preferred" to "least preferred." Each supermarket is treated as an irreducible unit identified by name only.

Each respondent then rates each local supermarket on the basis of the three attributes previously identified. Ordinal levels are defined for each attribute. Five price levels - 4 percent above average, 2 percent above average, average, 2 percent below average, 4 percent below average; five size levels - floor plan A, floor plan B, floor plan C, floor plan D, floor plan E; and five distance levels - one, three, five, seven, and nine miles - were chosen.

The third set of data contains respondent's ranking of 25 hypothetical grocery alternatives based upon a latin-square design of the same three attributes identically defined. Experimental grocery alternatives help ensure that choices are made with respect to uniformly cognized objects and minimize the difficulties of confusing preference and opportunity.

Information pertaining to the subject's shopping pattern is expressed as total purchases per month at each of the eight supermarkets.

Analysis

Kruskal's MONotonic ANalysis of VARIance (MONANOVA) is used to determine interval scale weights for attributes assumed to be important in the preference function for hypothetical grocery alternatives [12]. The algorithm performs an additive analysis. Scale weights are derived in the following manner:

$$(4) U(x_i) = \sum_{j=1}^n w_j x_{ij}; \quad i = 1, 2, \dots, n; \quad j = 1, 2, \dots, m$$

where the w_j denote the importance of each attribute j and are viewed as part worths of a utility scale that can be summed to yield a single (overall) utility. This is the same as saying:

¹This data has been made available by the Marketing Department, School of Business, Indiana University (Bloomington).

$$(5) U(x) = U_1(x_1) + U_2(x_2) + \dots + U_m(x_m)$$

Thus, the decision rule is simple conceptually and states that a respondent's total utility for a multiattribute alternative is equal to the sum of part worth utilities for the attributes.

THE COMBINATION RULE

Scales are constructed for each individual. Nine respondents with large stress values are eliminated from further consideration. Stress values for the remaining subjects vary from .000 to .199 with a mean value of .033.

A two-stage procedure is employed to more fully evaluate the additive combination rule. In stage one, weights derived from the ranking of hypothetical grocery alternatives are assigned to each local supermarket based on a respondent's rating for that store. The substitution is justified when attributes are identically defined in both cases. The assignment process is illustrated as follows: (See also Figure 1).

- (1) Each subject rank orders 25 hypothetical grocery alternatives defined over the three attributes - price, size, and distance. Responses are then scaled by the algorithm MONANOVA. The measurement values obtained for a specific individual, i , are presented in Figure 1. In this case, slight degeneracy is evident in the values for the attribute size.
- (2) Each individual also rates the eight local supermarket alternatives (G1-G8) on the basis of identically defined attributes. The ratings of individual i are shown in the figure.
- (3) MONANOVA scale weights from step one are then substituted for the ordinal ratings of the actual supermarkets from step two. An overall utility value for each outlet is computed. For individual i , the "most preferred" supermarket based on the assignment process is G2.

The assignment process is repeated for all 69 subjects. Thus, in a straightforward manner we are able to derive measurement values for supermarket attributes.

In stage two, aggregate stated and derived preference orderings are compared. The stated ordering is computed by averaging individual preference rankings for supermarkets (Data Set 1) across stores. The derived ordering is obtained by averaging calculated utility values (as in Figure 1) across stores. The correlation between stated and derived preference orderings is calculated by Spearman's r_s , see Table 1. The value of .8333 is significant at the .01 confidence level.

FIGURE 1: Assignment Process for Individual i

Step One - Sample MONANOVA Results

	<u>Level</u>				
	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>
Distance	-2.407	-1.204	0.000	1.204	2.407
Price	-0.385	-0.193	-0.096	0.241	0.433
Size	0.193	0.096	-0.096	-0.096	-0.096

Step Two - Supermarket Ratings

<u>Supermarket</u>	<u>Attributes</u>		
	<u>Distance</u>	<u>Price</u>	<u>Size</u>
G1	1	4	3
G2	3	4	3
G3	1	2	3
G4	2	2	3
G5	3	3	3
G6	1	2	4
G7	3	2	4
G8	1	1	4

Step Three - Substitution and Derivation of Overall Utility

<u>Supermarket</u>	<u>Derived Utility Values</u>			<u>Overall Utility</u>
	<u>Distance</u>	<u>Price</u>	<u>Size</u>	
G1	-2.407	0.241	-0.096	-2.262
G2	0.000	0.241	-0.096	0.145
G3	-2.407	-0.193	-0.096	-2.696
G4	-1.204	-0.193	-0.096	-1.493
G5	0.000	-0.096	-0.096	-0.192
G6	-2.407	-0.193	-0.096	-2.696
G7	0.000	-0.193	-0.096	-0.289
G8	-2.407	-0.385	-0.096	-2.888

TABLE 1: Stated/Derived Preference Orderings

Stated Preference Ordering	Derived Preference Ordering
G2	G2
G4	G4
G8	G1
G3	G3
G1	G8
G5	G7
G6	G5
G7	G6

Spearman's $\underline{r} = .8333$ Significant at .01 level

COLLECTIVE PREFERENCE FUNCTIONS

Aside from the measurement problem, it is interesting to examine the attributes as components of an expressed preference function. The relative importance of an attribute may be defined as that proportion of the total variation in the scale weights accounted for by that particular attribute. To examine the unique contribution of each attribute, a ratio scaled transformation of the MONANOVA scale weights is accomplished. The coefficients of the transformed scale weights represent the part worths of each attribute in defining a preference function for supermarkets.

Respondents are divided into two client groups. The grouping criterion is the store in which the highest percentage of purchases is made. Members of the first group are customers at urban supermarkets in commercial districts; the second group are customers at suburban supermarkets in predominantly residential areas. Thirty-one shoppers are identified for city supermarkets (G1, G3, G6, G8) and 38 for suburban supermarkets (G2, G4, G5, G7).

Collective preference functions are defined for each client group by averaging individual MONANOVA results and then performing the ratio scaled transformation, see Table 2. The collective preference functions for urban and suburban shoppers are summarized as follows:

$$(6) \quad U(X_U) = .438(D) + .427(P) + .135(S) \\ U(X_S) = .442(S) + .335(D) + .223(P)$$

Shoppers who patronize urban supermarkets are primarily concerned with distance and price; size represents a lesser dimension. By comparison, suburban shoppers are sensitive to size and distance with size emerging as the dominant attribute. The numerical analysis suggests that basic differences occur in attribute evaluation between urban and suburban consumer groups.

Discussion

The analysis linking stated and derived preference rankings suggests that respondents tend to process information according to the axioms of the additive conjoint measurement model. However, our conclusion is a tentative one. The fact that more complex models (e.g., polynomial expressions) were not examined here limits our findings both methodologically and substantively. The possibility that subjects may be using more complex processing models is acknowledged. This inquiry, therefore, must be viewed more as a prototype for future investigation than as a definitive statement pertaining to the measurement of consumer preference.

Additionally, differences in preference functions are identified for two groups of consumers, defined on the basis of patronage. While the grouping criterion employed herein is arbitrary, systematic clustering and the identification of collective preference functions is clearly possible [18]. The significance of this line of research stems from the desire of scientists interested in spatial themes to contribute to the understanding of large scale geographic pattern and process.

TABLE 2: Collective Preference Functions

Urban Shoppers					
	Level				
	1	2	3	4	5
Distance	-1.241	-1.130	.121	.926	1.427
Price	-1.307	-.831	-.071	.834	1.337
Size	-.420	-.136	.000	.012	.416

Suburban Shoppers					
	Level				
	1	2	3	4	5
Distance	-1.060	-.772	.008	.685	1.111
Price	-.664	-.335	-.089	.545	.801
Size	-1.301	-.879	.056	.992	1.564

We conclude this paper on a methodological note. This study suggests that a next step in consumer behavior research might focus on the psychological factors determining a subject's structure of preferences. Insights into these effects would have enormous consequences in modeling behavior based upon an expressed set of preferences. The study of preference functions by using decomposition models offers a new methodology for the study of combination rules, with potential for deeper theoretical and empirical analysis. The present paper is a necessary first step in this area to develop alternate rules of spatial choice.

REFERENCES

1. Anderson, Norman H. "Functional Measurement and Psychophysical Judgment," Psychological Review, 77 (1970), 153-170.
2. Brummell, A. C. and E. J. Harman. "Behavioral Geography and Multi-dimensional Scaling," Discussion Paper No. 1, Department of Geography, McMaster University, 1974.
3. Burnett, Pat. "The Dimensions of Alternatives in Spatial Choice Processes," Geographical Analysis, 5 (1973), 181-204.
4. Burnett, Pat. "The Dimensions of Alternatives in Spatial Choice Processes: A Reply," Geographical Analysis, 7 (1975), 327-334.
5. Cadwallader, Martin. "A Behavioral Model of Consumer Spatial Decision Making," Economic Geography, 51 (1975), 339-349.
6. Cesario, Frank J. and Tony E. Smith. "Directions for Future Research in Spatial Interaction Modeling," Papers of the Regional Science Association, 35 (1975), 57-72.
7. Coombs, C. H. A Theory of Data, New York: John Wiley and Sons, Inc., 1964.
8. Fiedler, John A. "Condominium Design and Pricing: A Case Study in Consumer Trade-Off Analysis," in Proceedings, Third Annual Conference, Association for Consumer Research, 1972, 279-293.
9. Green, Paul E. and Yoram Wind. Multiattribute Decisions in Marketing: A Measurement Approach, Hinsdale, Ill.: The Dryden Press, 1973.
10. Johnson, Richard M. "Trade-Off Analysis of Consumer Values," Journal of Marketing Research, 11 (1974), 121-127.
11. Kruskal, Joseph B. "Nonmetric Multidimensional Scaling: A Numerical Method," Psychometrika, 29 (1964), 1-27.
12. Kruskal, Joseph B. and F. Carmone. "Use and Theory of MONANOVA, a Program to Analyze Factorial Experiments Estimating Monotone Transformations of the Data," Bell Telephone Laboratories, Murray Hill, New Jersey, 1968 (mimeo).
13. Lancaster, Kelvin J. "A New Approach to Consumer Theory," Journal of Political Economy, 14 (1966), 132-157.
14. Luce, R. Duncan and John W. Turkey. "Simultaneous Conjoint Measurement: A New Type of Fundamental Measurement," Journal of Mathematical Psychology, 1 (1964), 1-27.

15. Louviere, Jordan J. "Predicting the Evaluation of Real Stimulus Objects from Abstract Evaluation of Their Attributes: The Case of Trout Streams," Journal of Applied Psychology, 59 (1974), 572-577.
16. Louviere, Jordan J. "The Dimensions of Alternatives in Spatial Choice Processes," Geographical Analysis, 7 (1975), 315-326.
17. Massam, B. H. and D. Bouchard. "A Comparison of Observed and Hypothetical Choice Behavior," Environment and Planning A, 8 (1976), 367-374.
18. Proserpi, David C. and Harry J. Schuler. "An Alternate Method to Identify Rules of Spatial Choice," Geographical Perspectives, 38 (1976), 33-38.
19. Quandt, Richard E. and William J. Baumol. "The Demand for Abstract Transport Modes: Theory and Measurement," Journal of Regional Science, 6 (1966), 12-26.
20. Rushton, Gerard. "Analysis of Spatial Behavior by Revealed Space Preferences," Annals of the Association of American Geographers, 59 (1969), 391-400.
21. Samuelson, Paul A. "Consumption Theory in Terms of Revealed Preference," Economica, 15 (1948), 243-253.
22. Shepard, Roger N. "A Taxonomy of Some Principal Types of Data and of Multidimensional Methods for Their Analysis," in Multidimensional Scaling: Theory and Applications in the Behavioral Sciences, Volume 1 (R. N. Shepard, et al, eds.), New York: Seminar Press, 1972.
23. Tversky, Amos. "A General Theory of Polynomial Conjoint Measurement," Journal of Mathematical Psychology, 4 (1967), 1-20.
24. Young, Forrest W. "A Model for Polynomial Conjoint Analysis Algorithms," in Multidimensional Scaling: Theory and Applications in the Behavioral Sciences, Volume 1 (R. N. Shepard, et al, eds.), New York: Seminar Press, 1972.