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Abstract

In this paper we propose a model for describing consumer decision making among assortments or menus of options from which a single option will be chosen at a later time. Central to the derivation of the model is an assumption that consumers are uncertain about their future preferences. The model captures both the utility of the items within the assortments as well as the flexibility the items offer as a group. We support our model empirically with two laboratory experiments. In the first experiment we test the underlying assumptions. In the second, we compare the predictive validity of our model to that provided by other models suggested in the literature.

Disciplines

Behavioral Economics | Business | Cognition and Perception | Cognitive Psychology | Experimental Analysis of Behavior | Marketing

Modeling Choice Among Assortments

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In this paper we propose a model for describing consumer decision making among assortments or menus of options from which a single option will be chosen at a later time. Central to the derivation of the model is an assumption that consumers are uncertain about their future preferences. The model captures both the utility of the items within the assortments as well as the flexibility the items offer as a group. We support our model empirically with two laboratory experiments. In the first experiment we test the underlying assumptions. In the second, we compare the predictive validity of our model to that provided by other models suggested in the literature.

Several researchers have found that many consumer decisions made in a retail setting are made in a sequential or hierarchical fashion (e.g., Bettman 1970; Bettman and Park 1980; Payne 1976; Wright 1974; Wright and Barbour 1977). In these types of decisions, an initial choice is made first among a set of assortments of options. Then, a single choice is made from the specific assortment selected in the previous choice. For example:

- one decides first which store or shopping mall to visit and then later chooses the specific item to purchase,
- one often makes reservations at a restaurant before the choice of the actual entree to be consumed is made.

In these types of decisions, decision-makers are able to make short-term predictions of the utilities of items in the choice set with considerable accuracy; however, they are less accurate in predicting their future preferences (Kahneman and Snell, forthcoming). Consequently, when a consumer is faced with a choice among various retail outlets, the consumer may prefer, *ceteris paribus*, the retail outlet that allows the most flexibility in the final decision. Flexibility would be desirable either because the consumer may wish to avoid decision conflict and thus put off ultimate choice until later (Simonson 1990) or because the consumer is uncertain

about future preferences (Koopmans 1964; Kreps 1979) and thus does not want to cut off some potentially desirable options at the first decision point.¹

In this paper, we propose a general model of assortment or menu choice that captures both the utility of the items within the assortment as well as the flexibility the items offer as a group. We report two experiments in which subjects are asked to make choices among retail assortments of various items. The first experiment tests the main postulates of our model. In the second experiment, we compare the predictive validity of our model to that provided by other models suggested in the literature. Results from both experiments support our proposed representation.

LITERATURE REVIEW

Description of assortment choice has not been specifically discussed in the retailing or consumer literature; however, there are areas of related interest. First, there is the literature concerning the uncertainty about future preferences or future choices. This literature is relevant because it points out some of the factors that should be considered in evaluating sets of options from which a future choice will be made. Second, there is the literature on modelling hierarchical choice, which indirectly relates to modelling choice among assortments. In hierarchical processes, choice sets are partitioned into two or more subgroups; then one subgroup is chosen and the others are dropped from consideration. The choice among the subgroups is thus similar to the choice among assortments, in that the subgroup represents a constrained group of options from which a single choice will ultimately be made. In traditional models of hierarchical choice, however, researchers do not specifically account for a significant separation of time between the choice of a subgroup and the final choice of an item. Finally, there is a large literature on choice models in which it is implicitly assumed that future preferences are stable. Hence, using these types of models one would predict that the utility of an assortment (from which only one item will be chosen) equals the utility of the maximum item within the assortment.

¹ Consumers may not always make choices in the sequential fashion represented by our above illustrations. For example, in making a choice among restaurants, a consumer may choose an entree and then go to a restaurant that offers it. However, as we discuss later in the paper, this type of choice process (which we later characterize as the Max Item model) is a special case of our general model.

Uncertainty About Future Preferences

Several researchers have pointed out that although consumers may be fairly certain about their preferences in the present, they become less certain as they extrapolate these preferences into the future. For example, March (1978) points out that attitudes about possible outcomes in the future are not entirely predictable and the variance in the subjective probability distribution over possible future preferences increases as the time horizon is lengthened. Kahneman and Snell (forthcoming) present experimental results that show that although people are knowledgeable about their tastes in the present, they do not know much about their tastes in the future. Kreps (1979) explains this uncertainty about future preferences by first suggesting several rational reasons for the uncertainty; e.g., the mood in the future may be different, tastes may depend on items consumed immediately before the decision period. As a result of this uncertainty about future preferences, consumers take actions in the present to insure the preservation of options in the future (March 1978). Kreps (1979) presents a representation theorem that suggests why a consumer may want to maintain flexibility for the future if s/he acknowledges “uncertainty about future tastes,” even if the uncertainty were not explicit.

It is important to distinguish between the “uncertainty for future preference” and more traditional uncertainty. For example, McAlister (1979) presents a model for choosing among menus of options when retailers can decline to sell to certain users. In her examples, the reason a subject may choose a specific group of options, from which ultimately only one option will be chosen, is because of the uncertainty involved with obtaining any specific item. Her example is a student applying to a set of colleges rather than to just one because of the uncertainty involved in the acceptance procedures. In our examples of choice among assortments, we do not consider this type of uncertainty—the consumer knows he or she can have any of the options with certainty, uncertainty exists with respect to future preferences.

In addition to the uncertainty about future preferences, a consumer may desire to maintain options in the future because of a desire to avoid the conflict of making a choice in the present. Therefore retail assortments that contain a variety of items allow the consumer to put off a decision until later and thus avoid conflict in the present (Simonson 1990). Consumers may also desire to maintain options in the future because of the desire to consume a portfolio of product attributes to maximize utility (Farquhar and Rao 1976).

In summary, this literature suggests that when choosing among assort-

ments from which a single choice will be made in the future, consumers may look for the set of options that offers flexibility because of uncertainty about future preferences, even if preferences are known with relative certainty in the present.

Hierarchical Choice Processes

As mentioned above, when we describe consumer decision processes as a hierarchical choice (McFadden 1978, 1986; Tversky 1972; Tversky and Sattath 1979) or sequential elimination process (Bettman 1970; Bettman and Park 1980; Wright 1974; Wright and Barbour 1977), we are indirectly talking about choices among assortments. However, there are two major differences between traditional models of hierarchical processes and modelling the assortment choice cited here. First, in our examples there is some time lag (even if it is only minutes) between the choice of the assortment and the ultimate choice of the item; in traditional models of hierarchical choice processes the time between these decisions is not considered a significant variable. Second, in modelling hierarchical choice processes the initial subgroups are formed based on the natural or intrinsic structure of the choice alternatives (for example, by similarity). Assortments within stores, on the other hand, are generally constructed by some extrinsic method. There are examples of hierarchical choice processes in the marketing and consumer behavior literature that allow the initial subgroups to be formed by an extrinsic method (Hauser 1986; Kahn, Moore, and Glazer 1987) but again in these examples the researchers assume that the time between the successive choices is not a significant variable.

Nested Logit Model

One formal representation of the hierarchical choice process that is frequently used to model these types of decisions is the Generalized Extreme Value (GEV) or nested logit model (McFadden 1978). McFadden has shown that the choice probability for choosing an item in this type of situation can ultimately be simplified to:

$$P_{item} = P_{item/subset_i} \times P_{subset_i}$$

$P_{\{subset\ i\}}$ is equivalent to what we are calling the probability of choosing a specific assortment from which only one will ultimately be chosen. The $P_{\{subset\ i\}}$ is expressed in the GEV model as the utility of subset i divided by

the sum of the utilities of all subsets in the original choice set. Here we focus on the *utility* of the subset, which is:

$$Utility_{subset_i} = K_i + \lambda_i \ln \sum_{j \in subset_i} e^{Y_j}$$

where:

- K_i = a constant that represents the unique attributes of subset i
- Y_j = the utility of alternative j in subset i , and
- λ_i = normalizing constant.

In this formulation the utility of the assortment is expressed as the natural log of the sum of a function of the utilities of the individual items within the set, plus a constant. The basic assumption used to derive this expression is that the decision maker equates the utility of the subset with the utility of the most preferred item; however, there is some uncertainty as to which item has the maximum utility because there is uncertainty associated with the utility of each item. Therefore, more than just the utility of any one item is taken into account in deriving the utility of the whole set of items.

Models with Stable Future Preferences

Another way to model the assortment decision is to assume the consumer has stable future preferences that are known with certainty; for example, constant utility models (Luce 1959). If this were the case, the utility of a set of options from which only one item would ultimately be chosen would rationally be equal to the utility of the most preferred item. Retailers frequently make this assumption. For example, in considering how consumers react to the options provided in a product line, Green and Krieger (1985) assume that the buyer's utility for a product line is equal to the utility he or she derives from his or her first choice item. This suggests that each buyer will be indifferent among assortments that offer different varieties of options as long as each of them contains his or her first-choice option in their set. Therefore, according to this theory, the chief reason to offer variety in a retail offering is to appeal to the heterogeneity of tastes in the target population.

Summary

As this review reveals, the simplest way to model the choice among assortments from which only one item would ultimately be chosen is to

assume that the consumer has stable preferences and will choose the set with his or her favorite option. This issue is more complicated if one assumes, as is done in hierarchical models of choice, that there is some uncertainty associated with the utility of each item even in the present. Using this assumption, one would model the utility of an assortment as the natural log of the sum of a function of the utilities of the individual items within the assortment. These two formulations will serve as referent models for our representation.

A MODEL OF ASSORTMENT CHOICE

Background

Conceptually, we postulate that when consumers choose among menus or retail assortments they are looking for the set of options that maximizes their chances of having their most preferred option in the future. To model this, we assume that individuals act as if they want to choose that assortment that offers both preferred items and flexibility. There are two elements of a set that may contribute to flexibility. One element is the *number* of acceptable options. The other element is the portfolio of options available—a *varied* portfolio of acceptable options increases the likelihood of obtaining the option most preferred in the future.

Number of Options. As Wright and Barbour (1975) point out, a decision maker intuitively realizes that a larger pool increases his or her chance for an optimal choice. Reibstein, Youngblood, and Fromkin (1975) show empirically that perceived decision freedom increases as the number of options in the choice set increases. Finally, Glazer, Kahn, and Moore (1991) show that the number of items offered in a choice set influences the final *choice*. Thus, the mere number of options represents a type of flexibility. For example, an ice cream parlor that offers 31 flavors seems to offer more flexibility than an ice cream parlor that offers 3 flavors, no matter what the flavors are. This leads to the first postulate underlying our model:

Postulate 1: Preference for an assortment of items is enhanced by including additional acceptable items to the assortment.

While the number of acceptable options will add to the value of the assortment,² the number of unacceptable items may detract from the value.

² There could potentially be too many acceptable items, which would detract from the value of the assortment; but we will not consider such large assortments in this paper.

This could be due to the cost of the time it would take to evaluate them. In addition, the unacceptable items may serve as a signal that the whole assortment is unattractive. Moreover, having negatively valued items in the assortment may bring negative associations to mind which individuals may prefer to avoid. We allow for a negative impact of unacceptable items in our model.

Type of Options. We assume that preference for an assortment is increased as the preference for the items in the assortment increases. That is, it is not just the number of acceptable alternatives but also their value that increases preference for an assortment. This leads to the second postulate:

Postulate 2: Holding number of items within the assortment constant, assortments with higher-valued individual items are preferred to assortments with lesser-valued individual items.

Variety of Options. One way to maintain flexibility is to have a varied portfolio of acceptable options in the future-choice set. Intuitively a more attractive portfolio would include both more preferred options and more variety (or less similarity) among the options. In support of this intuition, researchers have found that in a product evaluation task some moderate level of unexpectedness or distinctiveness is valued and sought out (see Meyers-Levy and Tybout 1989 for discussion). This leads to the third postulate:

Postulate 3: When two items that are equally preferred are added to an assortment, the item that is more dissimilar, or more unique, with respect to the existing assortment adds more to the value of the assortment.

The perceived uniqueness³ of the added item will be a function, to some degree, of the number of items within the assortment. For example, assume a retail outlet offered four chocolate bars. The first one is by definition the most unique; the second one considered then has the opportunity to offer the most additional uniqueness over the remaining two bars. The fourth chocolate bar has very little opportunity to offer any unique attributes. Thus the relative uniqueness of adding the second chocolate bar to the assortment (which at this point would consist of only one other chocolate

³ We use the term uniqueness, rather than dissimilarity or distinctiveness, because the latter terms (or more specifically, their opposites, similarity and substitutability) are generally used with regard to pairwise comparisons. We are considering the uniqueness of an item with respect to an *assortment* rather than with respect to just one other item.

bar) is higher than the relative uniqueness of adding a fourth chocolate bar to the assortment. Thus we augment the third postulate:

Postulate 3a: Any given item will be more unique, and hence add more, to a smaller as opposed to a larger assortment.

In addition, we note that the amount of uniqueness an item can add to an assortment depends on its level of utility and vice versa. In other words, if a brand is totally unique to the assortment but has zero utility, it will add nothing to the assortment. Similarly if an item has a high utility, but is exactly the same as an existing item in the assortment (thus offering no uniqueness), it will again add nothing to the assortment. Thus, the next postulate is:

Postulate 3b: There is an interaction between preference of the option and the amount of uniqueness the option offers to the set.

General Model

Presented below is a mathematical representation of value of an assortment or set of options that captures the properties discussed above. The first term in this model represents the combined impact of preference and uniqueness of the items in the assortment on the value of the assortment, consistent with postulates 2, 3a, and 3b. This term is a sum which is computed by first taking the utility of the most currently preferred item. Then the utility of the next most preferred acceptable item, weighted by the additional uniqueness it contributes in relation to the most preferred item, is added. Then the utility of the third most preferred acceptable item, weighted by the additional uniqueness it contributes in relation to the first and second more preferred items, is added, and so forth until all the acceptable items are considered. The second term represents the impact of the number of acceptable items as described in postulate 1. The third term allows for a possibly negative impact of the inclusion of unacceptable items in the assortment. Thus we expect c_1 to be positive and c_2 to be negative. Mathematically,

$$V_{set} = \sum_{j \in A} p_j U_{j|1 < j} + c_1 n_A + c_2 n_N \quad (1)$$

V_{set} = value of the assortment or set of options

p_j = utility of the j th acceptable item in the set where j indexes preference order; i.e., 1 is most preferred and n is the least preferred acceptable item in the set

- A = subset of acceptable items in the assortment
 $U_{j|i < j}$ = uniqueness of item j in relation to the $j-1$ more preferred items in the acceptable set which are indexed i
 n_A = number of acceptable items
 n_N = number of unacceptable items
 c_k = importance of number of items

Following postulate 3b, the first term in the model makes a strong assumption about the way in which utility and uniqueness are combined. We postulate that the consumer acts as if he evaluates the portfolio of options in the following way. Although the consumer may not know which option will be preferred in the future, we start with the premise that it is known with certainty which option is preferred in the present. Our model assumes that in assessing the utility of the assortment, the consumer acts as if s/he first considers the currently most-preferred item. Then the model assumes that the consumer considers the next most-preferred item. If the second item offers no uniqueness and is perfectly substitutable for the first, then the second option adds nothing (since the first item will always produce the highest value). If the second option is somewhat unique and therefore offers some variety, then it might be better in the future and hence ultimately add some value. If the second option is totally nonsubstitutable (completely unique), then the second item adds the most value since a craving for the first item is likely to be accompanied by a lack of desire for the second or vice versa. Similarly the third most-preferred item's contribution to the value of the assortment depends both on its utility and its uniqueness from the two most preferred, and so forth.

In this model, the c_k parameters and the number of acceptable items in the set would vary by individual and the perceived level of uncertainty in each situation. For example, if there were no uncertainty in the situation, either because the time of the next stage of the decision process was instantaneous or because there was no uncertainty in future preferences, then c_1 and c_2 would be zero and the only acceptable item in the set would be the item with the maximum utility. Hence, the utility of the assortment would equal the utility of the most preferred item. On the other hand, if there is a great deal of uncertainty in the situation then c_1 , the coefficient of the *number* of acceptable items in the set, might be high.

While this model has the conceptual properties we seek, it has numerous parameters to estimate. If there are T acceptable alternatives in the choice set, there are T values plus $T-1$ uniqueness values plus two parameters which equal $2T + 1$ parameters to estimate. Given this, it is desirable to use a constrained version of the model, which has fewer parameters.

Constrained Model

This model uses information gathered outside the assortment selection process to calibrate the model. We assume that consumers can evaluate options in the present but are uncertain about the future. Specifically, the p_j s and U_j s are estimated outside the model.

First, we ask the subjects to indicate which are the acceptable items in the set. We then ask the subjects to indicate their preference of an item given it is the only item in the assortment. The utilities of the T acceptable alternatives can be measured by a variety of means (e.g., 0–100 scales; six-point like-dislike scales). Here we assume the values (P s) given by this type of method relate to the p s by:

$$p = a + bP$$

This reduces to two the number of value parameters to be estimated from T : a and b .

To estimate uniqueness, we ask the subjects to indicate how substitutable or similar one item is to another. These substitutability scores, which ultimately generate the uniqueness scores, can be derived by asking subjects to evaluate the attribute structure of each of the items. Items are considered more substitutable or more similar based on the number of attributes they have in common (Lattin and McAlister 1985). For each pair of items we compute a substitutability measure that equals the number of attributes shared divided by the total number of attributes considered. Thus our substitutability measures range from 0 to 1. In measuring preference of an item and similarity of that item to another we are assuming independence of these two constructs, a frequent assumption in choice modelling (Batsell and Polking 1985; Currim 1982; Huber and Puto 1982, 1983; Kamakura and Srivastava 1984; and Tversky 1972).

The substitutability measures describe the relationship between the pair of items but do not indicate how each of the items relates with respect to all other items in the set. To obtain this additional information we compute correlations on the substitutability matrix. Given the resulting correlation matrix, the uniqueness, $U_{\{j/i<j\}}$ is the partial correlation of j , assuming the other $j-1$ more preferred options are already included in the assortment.

This process can best be demonstrated by example. In this hypothetical example, assume Coke and Pepsi are perfect substitutes, Dr. Pepper and Pepsi are perfect substitutes, and 7-Up is not a substitute for anything. In addition, Coke is the most preferred item, followed by Pepsi, Dr. Pepper,

and 7-Up.⁴ These relationships are represented by the following substitutability matrix:

	Coke	Pepsi	Dr. Pepper	7-Up
Coke	1	1		
Pepsi	1	1	1	
Dr. Pepper		1	1	
7-Up				1

Given the substitutability data, a table of “correlations” (constrained to be positive) can be derived using the following formula:

$$r_{ij} = \frac{s_i \cdot s_j}{|s_i| \cdot |s_j|}$$

where:

- s_i = row vector from the substitutability matrix
- $|s_i|$ = length of row i

This results in the following table of correlations:

	Coke	Pepsi	Dr. Pepper	7-Up
Coke	1	.82	.50	0
Pepsi		1	.82	0
Dr. Pepper			1	0
7-Up				1

The uniqueness, $U_{j|i < j}$, is then measured as 1 minus the squared multiple correlation of j to the $j-1$ more highly valued items. The uniqueness of the most preferred item is always 1. Mathematically,

$$U_{j|i < j} = 1 - R'_{ij} \cdot R_{ii}^{-1} \cdot R_{ij}$$

⁴ In this example substitutability is not transitive. We use this as an example to show that our measure can handle irrational responses from subjects. This intransitivity could occur because it is possible that brand 1 is not noticeably different from brand 2, and brand 2 is not noticeably different from brand 3; however brand 1 is noticeably different from brand 3. However, for all of our subjects, substitutability was transitive. Also, the data in the example are essentially binary, whereas measured substitutability is a continuous variable. We use the binary data to simplify the example.

where:

R'_{ij} = row vector of correlations of j th item with $j-1$ more valued items

$R_{ii}^{(-1)}$ = inverse of the correlation matrix among the $j-1$ more valued items

With these data, then

$$U_{Coke} = 1$$

$$U_{Pepsi|Coke} = 1 - (.82)^2 = .33$$

With the preferences and substitutabilities for the soft drinks estimated externally in this way, the constrained model can be written as follows:

$$U_{Dr.Pepper|(Coke,Pepsi)} = 1 - \begin{bmatrix} 1 & .82 \\ .82 & 1 \end{bmatrix}^{-1} \begin{bmatrix} .5 \\ .82 \end{bmatrix} = .25$$

$$V_{set} = \sum_{j \in A} (a + bP_j)U_{j|i < j} + c_1n_A + c_2n_N$$

Rewriting this we obtain,

$$V_{set} = a \sum_a U_{j|i < j} + b \sum_a P_j U_{j|i < j} + c_1n_A + c_2n_N \quad (2)$$

In this model, a , b , c_1 , c_2 can be estimated by ordinary least squares. We expect c_1 to be positive and c_2 to be negative. In this paper we focus on the constrained model. We next describe the two experiments we conducted that provide empirical support for the model.

STUDY 1

Method

In order to test the basic postulates of the model we ran an experiment on 41 undergraduate students who participated as part of a course requirement. In this experiment, each subject was shown 36 different snack foods organized by similarity groups. The snack foods and their groupings are listed in Table 1.⁵ Each subject was told that they would make a series of choices, which would be displayed on a computer terminal, between as-

⁵ Using a small sample of undergraduate students separate from the 41 subjects mentioned above, we ran a pilot test on these groupings of snack foods that indicated that there was significantly more variety between the groupings than there was within the groupings.

TABLE 1

Experiment One Stimuli

Chocolate Bars	Snack Crackers	Spicy Chips
Hersheys Milk	cheese/cheese	sour cream & chives chips
Milky Way	cheese/wheat	barbecue potato chips
Three Musketeers	cheese/rye	onion potato chips
Nestles Crunch	cheese/sesame	garlic potato chips
Mounds	Cheez Bits	Nacho Doritos
Butterfingers	Ritz Bits	Spicy Doritos
Health Food Bars	Sugarless Candy	Candy (non-chocolate)
Granola Nut Bar	gumdrops	red licorice
Choc. Granola Nut	peppermints	gummy bears
Oatmeal Nut	fruit mints	Chuckles
Oat Nut Raisins	peppermint gum	gum drops
Granola Nut & Cinn.	spearmint gum	candy corn
Oatmeal Nut & Cinn.	bubble gum	spearmint leaves

sortments of the snacks foods. The subjects were to imagine that these assortments represented vending machines of options. We used vending machines as the retail outlet so that all possible extraneous characteristics of a store, such as parking, layout, salespeople, and so forth would not enter into the decision. They were told that in a week, they would be offered the assortment in one of the vending machines they had chosen and would then be allowed to choose a single option which they could consume immediately. (Eighty-five percent of the subjects returned to get their snack food during the following week).

The first task the subject was asked to do was to rank order the six types of snack foods by their current preferences. Only the three most preferred groups of snack foods were used in the experiment, and these will be labelled for our purposes, A, B, and C, where A is the most preferred group. Each subject had different As, Bs, and Cs and the experiment was specifically tailored to represent the individual's preferences. Also, each subject used in the study indicated that they had purchased snack foods in the last year.

The experimental procedure then required the subjects to choose between all pairwise combinations of eight assortments, resulting in 28 comparisons. The eight assortments were comprised as follows:

- 6 A items
- 6 B items
- 2 A items

2 B items
 2 items = 1 A, 1 B
 2 items = 1 B, 1 C
 6 items = 3 A, 3 B
 6 items = 3 B, 3 C

These comparisons were presented on the computer in a unique random order for each subject. The comparisons were relatively easy for the subjects to make as they were familiar with the stimuli and the stimuli were available in the test room for further examination (but not consumption).

Independent Variables. These eight assortments represent a $2 \times 2 \times 2$ design. The first factor is number of options (six or two), the second factor is amount of uniqueness or variety offered by other options in the set (a little or a lot), and the third factor is preference (high or low). Notice that the preference manipulation is imperfect, as the total utility of 2 A items (not counting uniqueness) does not equal the total utility of the 1A and 1B items. This makes the manipulation of variety more conservative, since the assortments with more variety are penalized by a discount in the sum of the utility of the items. The individual items were distributed to the sets to minimize the correlations among the items appearing in the same assortment.

Dependent Variable. The dependent variable in this analysis is the total number of times each of the eight sets was chosen in the paired comparisons with the seven other sets. Each assortment could thus receive at most 7 points and at least 0 points. The subjects were allowed to indicate indifference. If they did, each of the two sets was assigned a half-point.

Based on our assumptions of the model we would expect:

- A significant main effect due to number of items in the set (Postulate 1).
- A significant main effect due to preference of items in the set (Postulate 2).
- A significant two-way interaction: variety \times number (Postulate 3a).
- A significant two-way interaction: preference \times variety (Postulate 3b).

Results

We analyzed the results using repeated measures of analysis of variance. We found direct support for three of our postulates and indirect support for the fourth. (See Table 2). The number of options in the set was significant

TABLE 2
Mean Preferences for Assortments in Experiment One

Assortment	<i>N</i>	Mean Dependent Variable
Two-Way Interaction: variety × number^a		
Low Number:		
Low Variety	82	2.5
High Variety	82	2.2
High Number:		
Low Variety	82	4.6
High Variety	82	4.7
Three-Way Interaction: variety × number × preference^b		
High Preference Assortments:		
2A	41	3.5
1A1B	41	2.9
6A	41	5.8
3A3B	41	5.9
Low Preference Assortments:		
2B	41	1.6
1B1C	41	1.5
6B	41	3.4
3B3C	41	3.5

^a Where maximum dependent value = 6.5 and minimum value = 0.5
^b Where maximum dependent value = 7 and minimum value = 0

($p < .0001$) with six options preferred to two options [mean(6) = 4.6, mean(2) = 2.4, where the maximum possible is $(7 + 6 + 5 + 4)/4 = 5.5$ and the minimum possible is $(0 + 1 + 2 + 3)/4 = 1.5$]. We also found a significant main effect for preference ($p < .0001$) with assortments with high preference items being preferred to assortments with low preference items [mean (high) = 4.5, mean (low) = 2.5, again where the maximum possible is 5.5 and the minimum possible is 1.5]. In addition, we found a significant two-way interaction, variety × number ($p < .05$). The two-way interaction, preference × variety analyzed to test Postulate 3b, was not significant ($p > .30$). However, we found a significant three-way interaction, preference × variety × number ($p < .0001$). The means

for the eight assortments are shown in Table 2 (where maximum value = 7 and minimum value = 0). This three-way interaction includes a cross-over effect, which thus explains why the two-way interaction used to test Postulate 3b was not significant.

One way to interpret this three-way interaction is as follows. For a set with two A items, the second A item still offers some variety, so its high utility is not discounted much. Consequently two A items have more utility than one A item and one B item since the B item in the second set does not offer as much utility as an A item. However, when we get to assortments with six options, the fourth, fifth, and sixth A items are no longer adding much variety, so the subject prefers an assortment with items whose individual utilities are not quite as high but that offers more variety. Hence three A and three B items are preferred to six A items *even though the sum of the individual utilities (not weighted by the uniqueness) in the former assortment would be lower*. In addition, variety offers more of a relative boost to sets with a large number of lower preference items than to sets with a small number of higher preference items.

This result is consistent with our representation; i.e., subjects consider the utility of their most preferred item in the assortment and then add to it the utility of the remaining items in the assortment weighted by the amount of uniqueness or variety those additional items offer. Thus the second chocolate bar is not discounted much because it still offers some uniqueness (e.g., nuts), but by the fourth chocolate bar there is little uniqueness offered that is not captured by the first three chocolate bars.

STUDY 2

We designed a second experiment to test the predictive power of our model as compared to several simpler reference models. Based on the review of existing models, we chose the following to serve as reference models:

1. Value of Set = Utility of most-preferred item (as suggested in Green and Krieger 1985), and
2. Value of Set = Natural log of the sum of a function of the utilities of the acceptable items in the set (as suggested in McFadden 1978).
3. Value of Set = the sum of utilities of all of the acceptable items in the set (a linear version of McFadden 1978).

The first model is nested in our model by constraining c_1 and c_2 to equal zero and U_i to equal 1 if i equals 1 and to equal zero otherwise. The second

model is not nested in this model. The linear version of the model is nested by constraining c_1 and c_2 equal to zero and U_i equal to one for all i .

Subjects

We had two sets of subjects for this study. The first were 31 MBA students. The data were collected in a marketing management class as part of a course requirement. After the questionnaires were completed, informal discussion with several students indicated that they had taken the assignment seriously and that they believed the task was realistic. Overall, we felt that the students had been motivated to answer the questions reliably. We test the assumptions of the model and the comparison of fit of our model to the reference models on these subjects.

The second set of subjects were 12 seventh-grade girls from a small east coast town. The data from these subjects were collected during a gathering specifically initiated for this task. The girls were rewarded with pizza for their participation in the survey. Since this subject pool is very different from the first, similar results would provide convergent validity for our conclusions.

Method

In this experiment subjects were told to assume that they expected to watch *one* television show *two days* from the present. Before they could watch the show, they had to choose among various cable services in the area. The services offered different menus of shows. Once they had selected a service, and hence an assortment, they could watch any one show from the selected set.

We chose to use television shows as stimuli for this experiment for several reasons. First, choosing among assortments of television shows was a plausible but not a common task, so subjects were unlikely to have preconceived ideas about the sets which might confound the experiment. For example, if we had chosen restaurant menus as the stimuli, subjects might be likely to include assumed traits of restaurants (e.g., ambience, price, etc.) in making their judgments rather than just considering the items on the menu *per se*. Second, we wanted to use stimuli that were realistic, easy to understand, and easy to form value judgments about, but not too familiar to the subjects. To do this, we ran our study during the second week of the fall television season. In addition to show names, we provided descriptions of the television shows (from *TV Guide*). Many subjects had not seen these shows yet or had not seen very many of them yet and so, most likely, no strong associations existed. However, based on the thor-

ough descriptions we gave of the shows, the subjects could determine which shows they would want to watch at that time. Thus uncertainty was which shows they would want to watch two days in the future. The 27 shows fell into three broad categories: detective, situation comedy, and sports shows.⁶

The subjects began by indicating whether each of the 27 television shows was acceptable or unacceptable and then rated each show on a 0–100 scale where 100 represented “would most like to watch” and 0 represented “most unwilling to watch.” Every subject in both subject pools indicated familiarity with the types of television shows that we were including in the experiment.

Then the subjects were asked to rate 27 assortments on a 0–100 scale where 100 indicated an assortment with which they were most satisfied and 0 indicated one with which they were most dissatisfied. The 27 assortments represented a replicated 3×3 factorial design where factor 1 was size (3, 6, or 9 shows) and factor 2 was variety (1, 2, or 3 show types). In our design, each size-type combination received 3 replications. The basic design appears in Table 3.

Each type of show, i.e., I, II, or III (detective, situation comedy, or sports), appeared in 18 assortments. While perfect independence was not attainable in allocating each group of 9 shows within a show-type of these 18 sets, allocations were made so as to minimize the correlations among items appearing in the same assortments. This was done by trying to insure that for the 17 assortments where there was a choice of which Type I shows to include (Assortment 18 included all 9 Type I shows), each pair of shows occurred together 2 or 3 times and that overall each show appeared in exactly 6 sets. The allocation of Type I shows to the 17 assortments is shown in Table 4. The same procedure was used for Type II and Type III shows. Each type of show was assigned separately and then the complete sets were constructed. Using this method, almost all of the correlations between pairs of shows in the design were less than 0.20.

After the subjects evaluated the assortments, they were asked to indicate whether each of the 27 shows was characterized by action, humor, violence, melodrama, romance, and sexiness. They could assign as many or as few attributes as they wanted to each show. This list of attributes was developed from a pretest. These ratings were used to form substitutability

⁶ In our scenarios each of these shows could be watched for the same length of time, even though in real life situation comedies are a half-hour long, detective shows are an hour long, and sports events vary.

TABLE 3

Basic Design of Assortments in Experiment Two

Number of Shows		3	6	9	
Variety	Low (1 type)	3I ^a	6I	9I	
		3II ^a	6II	9II	
		3III ^a	6III	9III	
	Med. (2 types)	1I,2II or 2I,1II	3I,3II	5I,4II or 4I,5II	
		1I,2III or 2I,1III	3I,3III	5I,4III or 4I,5III	
		1II,2III or 2II,1III	3II,3III	5II,4III or 4II,5III	
		High (3 types)	1I,1II,1III	2I,2II,2III	3I,3II,3III
			1I,1II,1III	2I,2II,2III	3I,3II,3III
			1I,1II,1III	2I,2II,2III	3I,3II,3III

^a I,II,III refer to the 3 types of shows

scores as described earlier. Then these substitutability scores were used to derive uniqueness measures.

Results

We used the data collected in the experiment described above to compare our assortment model with the three reference models. These model comparisons were made on the individual level and the results were aggregated across all individuals.

For the three reference models, the appropriate regressions were run for each individual across all the 27 assortments. In each case the dependent variable was the value (from 0 to 100) assigned by the subject to the assortment. The independent variables were constructed from the values the subjects gave to each of the acceptable shows within the set as appropriate for each model. We report the average R^2 s for all four models in Table 5.⁷

⁷ All models were run with constants forced to equal zero.

TABLE 4

**Allocation of 9 Type I Shows to 18 Sets, including Type I Shows in
Experiment Two**

Sets	1	2	3	4	5	6	7	8	9	No. of Type I Shows
1	1		1		1					3
2	1			1	1	1	1	1		6
3				1		1				2
4	1	1							1	3
5		1			1	1		1		4
6	1									1
7		1				1			1	3
8	1	1	1	1			1			5
9				1						1
10							1			1
11								1		1
12			1		1					2
13		1					1			2
14			1					1		2
15			1			1			1	3
16				1				1	1	3
17					1		1		1	3
18	1	1	1	1	1	1	1	1	1	9
Total	6	6	6	6	6	6	6	6	6	54

As Table 5 shows, all models do well in fitting the data. However, the "Assortment Model" fits the data best overall. In the MBA study, for 21 of the 31 subjects, the Assortment Model fits better than any of the other models. The average R^2 for the Assortment Model at .86 is higher than for any of the other models. Similarly, in the study of the 12-year-old girls, all the models fit the data well, but the Assortment Model provided the best fit overall. The average R^2 for the Assortment Model was .92 compared to .90 for the "Max Item" and "Nested Logit" model and .87 for "Sum of Values" Model. The Assortment Model had the best R^2 for eight of the twelve girls and tied for first for three of the girls.

As the reference models are simpler models, two tests were run to

TABLE 5

 R^2 for Assortment Model and Three Reference Models

	Assortment Model	Max Item Model	Sum of Values Model	Nested Logit Model
MBA Sample ($n = 31$)				
Number Times				
Best R^2	21		6	
No. of Ties for 1st	3	3	1	3
Average R^2	.86 (.85) ^a	.80	.81	.80
7th Graders Sample ($n = 12$)				
Number Times				
Best R^2	8	1		
No. of Ties for 1st	3	2	1	2
Average R^2	.92 (.90) ^a	.90	.87	.90
^a Adjusted R^2				

determine whether the Assortment Model fit significantly better. An F test was run⁸ i.e.,

$$\frac{\text{Additional } R^2/3}{(1 - R^2)/23}$$

where 3 is the difference in degrees of freedom between the complex model and each simpler model and 23 is the degree of freedom of the more complex model.

We only tested Sum of Values and Max Item models as the Nested Logit and Max Item models fit equally well and the Max Item model is nested in the Assortment Model. In the MBA study, for 17 of the 31 subjects for the Sum of Values model and for 20 of the 31 subjects for the Max Item model, the more complex Assortment Model is significantly better (with an average F -statistic for the Sum of Values model equal to 8.5 and for the Max Item model equal to 5.6 with the critical value, $F_{(3,23,.05)}$, equal to 3.03). In the seventh-graders study, for 7 of the 12 observations for the

⁸ The models are not strictly nested but rather one is a constrained version of the other, so this test is not strictly applicable; however it does provide beneficial insights.

Sum of Values model and for 5 of the 12 observations for the Max Item model, the more complex Assortment Model is significantly better.

We also measured the percentage of variance unexplained by each of the simple models that was explained by the more complicated Assortment Model. In this MBA study for 19 of the 31 Sum of Values models and for 24 of the 31 Max Item models, the complicated model explained more than 20 percent of the unexplained variance of the simple models. The average increase in explained variance is 27 percent for Sum of Values and 34 percent for the Max Item models. Therefore, the more complicated model did significantly better in the majority of cases. In the seventh-graders study, for 8 of the 12 Sum of Values models and for 7 of the 12 Max Item models, the complicated model explained more than 20 percent of the unexplained variance of the simple models.

In both subject pools, the Assortment Model fit the data best; however, in the MBA sample the Sum of Values fit the data second best, and in the seventh-grade-girl group the Max Item model fit the data second best. This provides more support for the use of the Assortment Model, as it seems to fit well across groups, whereas the appropriateness of a particular simple model seems to vary by group.

We should point out that the simplest model (the Max Item model) fit the data quite well and that the absolute increase in predictive power of the proposed model is small (adjusted R^2 increased .05). However, this increase is statistically significant. This is important, since we used fairly strong assumptions in constructing the constrained assortment model tested here and calculations based on reasonably noisy data. Future refined versions of the model may provide more dramatic improvements, though the R^2 s here may be approaching the attainable upper bound for survey-based preference data.

More insight into the Assortment Model can be obtained by examining the average coefficients of the independent variables across all individuals. (See Table 6). Although there may be some variance across individuals, since the models are meant to be estimated at the individual level, the average values of the coefficients are significantly different from zero, except for the coefficient of the $\sum_A U_j$ term. Further, the signs of all of the variables are in the predicted direction. The standardized regression coefficients, or beta weights, indicate that the sum of the values of the acceptable items in the assortment weighted by their uniqueness to the assortment is the most important term. Interestingly, on the margin, the negative impact of the number of unacceptable items is as large as (and for the 12 teenagers larger than) the positive impact of the number of acceptable alternatives.

TABLE 6
**Average OLS Coefficients for Assortment Model Across all
 Individuals by Subject Pool**

	$\Sigma_A U_j$	$\Sigma_A P_j U_j$	n_A	n_N
MBA Population:				
Average	4.04	.40	1.25	-1.08
Standard Error	2.7	.04	.61	.43
<i>t</i> -test (30)	1.5	9.3	2.05	-2.52
Standardized Regression Coefficients	.35	1.54	.22	-0.15
7th Graders Population:				
Average	12.6	.47	.67	-3.5
Standard Error	7.2	.08	.91	1.3
<i>t</i> -test (11)	1.8	5.7	.73	-2.7
Standardized Regression Coefficients	1.4	2.2	.13	-0.31

CONCLUSIONS

We posited a model for the value of an assortment that included the impact of preference of the individual items, the uniqueness each item added to the assortment, and the total number of items in the set. In the first experiment, we found empirical support for the assumptions of our model. We found a significant three-way interaction: number of options by variety of the options by preference of the options in the assortment. None of the simple, referent models proposed in the literature accounts for this interaction. Our representation of the choice process that individuals use to decide among assortments does account for it.

In addition, in the second experiment, in both samples, our model performed significantly better than several simpler models in more than half of the cases. This better performance resulted even though we measured uniqueness rather than estimating it from the data. Among the cases where the Assortment Model did not provide a significantly superior fit (although it was generally marginally better), no one other model provided a consistently better alternative.

The results suggest that consumers look at an assortment as more than just an offering of their most preferred item. It appears from our results that it is reasonable to assume that consumers evaluate assortments in terms of

their flexibility for future choice and the effort required to weed out the unacceptable alternatives. Therefore, the more unique, acceptable items the assortment offers and the fewer unacceptable items, the better the assortment. Although our results show flexibility in an assortment is positive, we cannot as yet ascertain whether this flexibility is desirable because of uncertainty in future preferences, as suggested by Kreps (1979), or because of the complexity of the choice task and thus the desire to put off the effort of making a decision into the future, as suggested by Simonson (1990). Separating out these nuances is a fertile area for future research.

There is a caveat with respect to our results. We chose a product class where the products are consumable and in which flexibility and variety are desirable. In some product classes, where brand loyalty is extremely high (and preference for a single item dominates all others) and knowledge of the items within the assortment extensive, we would expect the value of the most-preferred brand to contribute very heavily, perhaps exclusively, to the value of the assortment. Our results are clearly most applicable to:

- retail settings where flexibility or variety-seeking are features of the product choice (e.g., restaurants, ice cream parlors, snack food outlets, theaters, entertainment centers, etc.) where future preferences are more likely to be uncertain, or to
- retail decisions in which there is some perceived risk or unfamiliarity about the products (e.g., microcomputers, stereo equipment) where the flexibility to postpone the decision would be valuable to reduce decision conflict.

There are several directions in which this research can be extended. First, we used one specific measure of uniqueness (without transformation) and we assumed a linear transformation of preference. It might be fruitful in the future to try different measures of uniqueness and perhaps an optimal scaling transformation. In addition, it would be interesting to see how preferences vary when the consumer expects to sample from the assortment more than one time. In such situations, one would expect the value of the unique items to increase. Also, the model could be extended to incorporate other attributes of the retail outlet itself; i.e., include the ambience of the store, parking, etc. The effect of signalling could be considered. In other words, does a computer store that offers three types of brand-name computers signal a higher quality computer store than a store that offers a potpourri of brand name and "low cost" options. Another area that should be examined is how generalizable the model is to services. Finally, we could consider how assortments are evaluated when

the choice is a group decision rather than an individual one. All of these are interesting topics that can be developed by extending the basic framework presented in this paper.

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