CONSUMER DURABLES:
ACTUAL BUDGETS COMPARED
TO VALUE PRIORITY MODEL -
PRELIMINARY RESULTS AND
MANAGERIAL IMPLICATIONS

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ABSTRACT

This paper compares actual consumer budget priorities to predictions from the value priority model. The actual consumer budgets are obtained via personal interviews in which consumers are asked to indicate which durable goods they plan to purchase in 1983, in 1984, and in 1985 and to prioritize their purchases within each budget year. The value priority model hypothesizes that consumers will prioritize goods according to "value", that is, "utility" per dollar.

In order to operationalize the model empirically, we estimate the "utility" of each item via a linear program (LP) that combines disparate data types into a convergent estimation procedure. The data types we use for estimation are (1) reservation prices, the price at which a good leaves the budget; (2) purchase probability, the consumer's estimate of the likelihood he (she, or they) will actually purchase the good; (3) lottery order, an ordering of goods without regard to price; and (4) comparison lottery prizes, choices among combinations of goods. These utilities, when divided by price, allow a prediction of the priority order in the consumer's budget. The actual rank order budget priorities are compared to the estimated values to test the model.

The full data set contains three budgets (1983, 1984, 1985) for each of 170 consumers. This paper reports on the preliminary analysis of 23 budgets. Early results indicate that (a) the value-priority model is a reasonable descriptor/predictor of consumer durable purchasing behavior, (b) that convergent LP estimation is feasible and leads to new insights on data collection, and (c) that the best measure of utility varies by person, but overall, purchase probabilities appear to be the best data with which to estimate "utility" for the value-priority model.
In 1983 we undertook a major empirical study with the cooperation of an American automobile manufacturer. The study provided the data collection necessary to document the data collection methods used in Houser, Roberts, and Urban (1983). The study also introduced the estimation procedures and provided a preliminary empirical test of the model. We believe both the estimation procedures and the empirical test are important contributions.

The estimation procedure consists of linear programming (LP) to minimize a weighted sum of estimation errors. In this way, we can use multiple data sources such as a different aspect of the vehicle, and combining methods, e.g., structural equations (LISER), and path analysis. The results of the estimation allow us to use disparate measures (e.g., probability scales and paired comparison) directly in a unified estimation procedure. After estimating the utilities, predictive tests are carried out to test the sensitivity of the estimates. The preliminary empirical test of the model is important because of the growing scientific and managerial interest in consumer durable goods behaviors and their related progress. The main emphasis will be on estimating the latent factors and multiple period effects of the data collection methods.
By comparing our model's predictions to actual consumer budgets, we provide some initial and evolutionary evidence toward a marketing theory of consumer durable purchasing.

**THE BASIC MODEL**

We begin by presenting the single period consumer model. We indicate briefly extensions to multiple periods including borrowing, savings, depreciation, operating costs, trade-ins, and interproduct complementarity. Details are in Hauser and Urban (1982).

The consumer is faced with the following problem. He is asked to allocate a fixed budget among $n$ durable goods, and among all non-durable goods. Let $g_j$ for $j = 1, 2, \ldots, n$ be the amount of good $j$ he selects. Remember, $g_j$ is discrete, that is, an integral number of goods. If we represent his budget by $K$, the amount he spends on non-durable goods by $y$, the prices of the durable goods by $P_1, P_2, P_3, \ldots, P_n$, and his utility function by $U(\cdot, \cdot, \ldots)$, then the mathematical problem he is asked to solve is

\[
\text{maximize } U(g_1, g_2, g_3, \ldots, g_n, y) \\
\text{subject to: } \sum_{j=1}^{n} p_j g_j + y \leq K
\]

This is the standard microeconomic consumer behavior model. Depending upon the functional form of the utility function, the solution to problem (P1) can involve complex non-linearities and discretization effects. Exact solution of (P1) may be difficult even for advanced mathematical programming computer algorithms.

It is unlikely that consumers solve (P1) in its full complexity in everyday decision making. In fact, there are a variety of scientific literatures that suggest otherwise. Some example citations include new economic theory (Reiner, 1983), information processing theory (Sternthal and Craig, 1982), mathematical psychology (Tversky and Kahneman, 1974), social psychology (Johnson and Tversky, 1983), and marketing science (Shugan, 1980).

We note in Hauser and Urban (1982) that a very simple consumer decision rule will, in most realistic cases, lead to an allocation of the budget giving a value of utility very close to the maximum attainable utility. We call this rule the value priority algorithm.

**Value Priority Algorithm**

Suppose that the consumer can assign to each good a marginal utility, $u_j$, that represents the amount of utility he obtains from possessing that durable good.\(^1\) If the consumer considers more

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\(^1\)For now, assume that $u_j$ does not depend on the other items in the budget. We can relax this assumption later.
leaves the consumer implicitly to the approximation of a value of \( y \), which is often the only way that consumers can be said to allocate their budget to substitute goods and non-substitute goods. The consumer's utility function, therefore, is a function of the value of the goods consumed, rather than the goods themselves. We show in Figure 4 that there exists a point where the goods are allocated optimally, and that this point is a complex function of the other goods in the budget.
and the budget cutoff can be estimated from real data are empirical questions that this paper begins to address.

Extensions

Consumer problem PI is a simple one period allocation problem, but the idea extends readily to many realistic issues. For example, in a multiperiod problem with borrowing (savings) and depreciation, the "value" becomes the depreciated time stream of utility divided by the price in "current" dollars. The budget constraints for each period are also related via the interest rate.

Operating costs become an addition to the price, discounted over time; replacement (trade-ins) are modeled by computing net utility gain and net price; and complementarity is approximated by first order dependence on higher valued purchases. For details and equations see Hauser and Urban (1982).

DATA

The value priority model is formulated at the level of the individual consumer, thus, we need individual level data with which to test the model. In March, 1983, we were given the opportunity to obtain the necessary data.

An American automobile manufacturer planned to introduce a new automobile in Spring 1984 and, among other things, wanted to know with which durable products the automobile would compete. This automobile was a luxury model for upscale consumers and competition from vacations, second homes, pools, boats, and college tuition was a management concern.

Budget Task

To obtain budget information, we gave consumers a deck of cards in which each card represented a potential purchase. For example, these cards included college tuition, vacations, home improvements, major clothing purchases, landscaping, cameras and accessories, furniture, home fuel savings devices, dishwashers, color televisions, stereo systems, jewelry, etc. After an extensive pretest, we were able to identify 52 items that accounted for most purchases. (Consumers were given blank cards for additional purchases.)

Consumers first sorted these cards according to whether they (A) now owned the durable, (B) would consider purchasing it in the next three years, or (C) would not consider purchasing it in the next three years. Consumers next considered pile A, "currently own", and removed those items they would either replace or supplement by buying an additional unit. Finally, they selected from pile B, "would consider", and from the replacement/additional pile, those items for which they would specifically budget and plan. These items are now their budgetable durable goods.
Since our theory and the data are at the level of the individual consumer, this choice is made for an initial test of the theory. However, the specific durables and the magnitudes of the budget allocation, both husband and wife participated in making a joint interview."

EXPLANATORY MEASURES

Obtaining utility measures that can be used to infer value among product categories is a difficult task. Over the years, a variety of methods have been used to estimate utility. In 1981, researchers used regression analysis to estimate utility functions for various product categories. In 1984, we tried a different method including direct utility estimates, conjoint analysis, and imputation analysis. However, in 1982, we tried a different method including direct utility estimates, conjoint analysis, and imputation analysis. Among all items, we found four measures that appeared feasible and included in our interviews.

Reservation Price. The consumer was asked to specify the minimum price, which, as he, she, or they would no longer purchase the durable. The consumer was asked to imagine that he, she, or they had won a lottery and would be allowed to select a prize. They were then to rank the durables allocated to each...
year in the order corresponding to the order in which he, she, or they would choose a prize in the lottery. Note that this ordering will usually be different than the budget allocation ordering because price is not to be considered in this task.

Combination Lottery Prizes. The consumer was again told that he, she, or they had won a lottery, but this time the task was to choose among two pairs of prizes. For example, the consumer(s) might be asked to choose among receiving either (a) the first and fourth ranked prize, or (b) the second and third ranked prize. Consumers were asked up to eight such pairs or combinations for each budget year.

Example Respondent

Table 1 lists the actual data obtained from one respondent. This respondent, a 30 year old, married woman with three children and a $35,000 per year family income, has six durable goods in his 1985 budget. For example, she expects to purchase a $5,000 automobile with probability .70. This durable good is ranked first in the lottery prize question and has a reservation price of $10,000. If price were not an issue she would rather have the automobile plus a freezer than paid tuition plus a vacation.

For each respondent, there are three tables such as Table 1, one for each year.

<table>
<thead>
<tr>
<th>DURABLE</th>
<th>PRICE</th>
<th>RESERVATION</th>
<th>PURCHASE</th>
<th>LOTTERY ORDER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Automobile</td>
<td>$5,000</td>
<td>$10,000</td>
<td>.70</td>
<td>1</td>
</tr>
<tr>
<td>Furniture</td>
<td>2,000</td>
<td>4,000</td>
<td>.60</td>
<td>3</td>
</tr>
<tr>
<td>Tuition</td>
<td>2,000</td>
<td>5,000</td>
<td>.99</td>
<td>4</td>
</tr>
<tr>
<td>Movie Camera</td>
<td>500</td>
<td>1,000</td>
<td>.60</td>
<td>5</td>
</tr>
<tr>
<td>Vacation</td>
<td>1,000</td>
<td>1,500</td>
<td>.70</td>
<td>6</td>
</tr>
<tr>
<td>Freezer</td>
<td>300</td>
<td>500</td>
<td>.50</td>
<td></td>
</tr>
</tbody>
</table>

COMBINATION LOTTERY PRIZES

(1) Automobile, Freezer > Tuition, Vacation
(2) Automobile, Vacation > Tuition, Camera
(3) Tuition, Vacation > Furniture, Freezer
(4) Tuition, Freezer > Camera, Vacation
(5) Freezer, Vacation > Camera
(6) Tuition > Camera, Freezer
(7) Tuition, Freezer > Furniture

Convergent Linear Programming Estimation

Each of the measures in Table 1 provides information about utility...
The idea behind conventional LP estimation is quite simple. Each datum implies a relationship either among various utility values or among a set of data values. The relationship varies by data type, and it is used to select utility values that are consistent with the data. The estimated errors are then used to select the best data type, and so on. The objective function is the weighted sum of errors where the weights are determined by the analyst. We will now illustrate the specific mathematical relationships.

Subject to relationships implied by the value priority model. We will now illustrate the specific mathematical relationships.

\[
\text{minimize} \quad W^*_1 (\text{errors based on reservation price answers})
\]

\[
+ W^*_2 (\text{errors based on combination lottery price answers})
\]

\[
+ W^*_3 (\text{errors based on purchase probability answers})
\]
Because at the reservation price, the jth item just falls below the budget cutoff, \( \lambda \).

To include equation (1) as a relationship in an LP, we define "errors based on reservation price answers" as the absolute value of the difference between \( u_j/r_j \) and \( \lambda \), that is, \( |u_j/r_j - \lambda| \).

In linear programming mathematics, this becomes

\[
\text{errors based on reservation price answers} = e^+_{r_j} - e^-_{r_j}
\]  

where the constraint relationships are,

\[
\begin{align*}
(u_j/r_j) - e^+_{r_j} + e^-_{r_j} &= \lambda \\
0 &\leq e^+_{r_j} - e^-_{r_j}
\end{align*}
\]  

Equations (2) and (3) are the standard LP formulation for minimizing absolute error, e.g., Gass (1979, p. 320). If values for \( u_j \) and \( \lambda \) are estimated and \( u_j/r_j \) exceeds \( \lambda \), only \( e^+_{r_j} \) will take on a positive value because minimization of equation (2) in LP forces \( e^-_{r_j} \) to zero. If \( \lambda \) exceeds \( u_j/r_j \), only \( e^-_{r_j} \) will be positive.

Since the LP seeks to minimize \( e^+_{r_j} + e^-_{r_j} \) and since it can simultaneously set \( u_j \) and \( \lambda \), one trivial solution is to set all variables equal to zero. We avoid this problem by recognizing that utility, and hence \( \lambda \), are ratio scales and thus unique to a positive constant. Thus, we can set one utility value, or \( \lambda \), arbitrarily. In our formulations we set \( \lambda = 1 \), thus scaling everything in terms of dollars.

**Purchase Probability Relationships**

The purchase probability is the consumer's estimate of the probability that the durable good will actually be purchased in the budget period. It is based on the utility and price of the durable good but also upon unobserved events that make the purchase more or less favorable. If these unobserved events represent observation error, then, according to the value priority model, the probability of purchasing good \( j \) is given by:

\[
L_j = \text{Prob} \left( u_j/p_j + \text{error} \geq \lambda \right)
\]

That is, the likelihood of purchase \( L_j \) is the probability that the value \( u_j/p_j \) is greater than the budget constraint \( \lambda \) after adjusting for error.
Factored combinations of product characteristics, measured at different stages of the production process, are important for quality control. Equation (6) shows the relative error in the measurement of the product characteristics at different stages. The reader will notice that this data and the constraints satisfied by

\[ e_n < z_n \]

\[ z_n < t_n \]

are similar to the constraints satisfied by

\[ \forall i, j, k \in \mathbb{N}, \quad e_{ij} < z_{ij} < t_{ij} \]

It is necessary to establish the relationship between the measurement errors and the constraints. For example, it is clear that the measurement errors affect the constraints. Thus, the reader will notice that this data and the constraints satisfied by

\[ \forall i, j, k \in \mathbb{N}, \quad e_{ij} < z_{ij} < t_{ij} \]

are similar to the constraints satisfied by

\[ \forall i, j, k \in \mathbb{N}, \quad e_{ij} < z_{ij} < t_{ij} \]

In these calculations, \( I \) and \( I \) are observed and appropriate, as such, they play a role as a rank order of the double goods according to the lottery order of the double goods.

### Lottery Orders

\[ \gamma = \gamma_0 + \gamma_\theta = \left( \frac{d}{\theta (\theta I - 1)} \right) g(\theta) = \left( \frac{d}{\theta} \right) g \]

And the associated constraints are

\[ \gamma_0 + \gamma_\theta = \gamma \]

Errors based on purchase productivity equations are

\[ \frac{\partial (\gamma_0 + \gamma_\theta)}{\partial g} = \gamma \]

In this equation, the purchase productivity equation can be used to obtain the objective function and constraint. By definition, the gradient of the objective function (5) can be interpreted as

\[ \frac{\partial (\gamma_0 + \gamma_\theta)}{\partial g} = \gamma \]

As estimated, the logistic model shown in equation (5) where \( g \) is a parameter to be identified model shown in equation (5) because the exponential productivity distribution, does not work. Because the exponential productivity distribution, does not work.
Following similar methods, we count errors only when the inequality relationships are violated. That is,

\[ \text{lottery order error} = (1 - \delta_{jk}) e_+^{ojk} + (\delta_{jk}) e_-^{ojk} \]  \hspace{1cm} (9) \]

\[ u_j - u_k - e_+^{ojk} + e_-^{ojk} = 0 \]  \hspace{1cm} (10)

\[ u_j' - u_k' + e_+^{ojk} - e_-^{ojk} > 0 \]

where

\[ \delta_{jk} = \begin{cases} 1 & \text{if } j \text{ is preferred to } k \\ 0 & \text{if } k \text{ is preferred to } j \end{cases} \]

In equations (9) and (10), the (0, 1) variable, \( \delta_{jk} \), is the "answer" to the lottery order question which tells us which product is preferred as a prize in the lottery.

Unlike Srinivasan and Shocker (1973), we need not worry about the scaling of the utilities because their scaling is already established by the constraints associated with the reservation price and purchase probability data.

**Combination Lottery Prizes**

The combination lottery prize questions imply rank order relationships among pairs of utilities. For example, if the combination of goods 1 and 4 are preferred to the combination of goods 2 and 3, then

\[ u_1 + u_4 \geq u_2 + u_3 \]  \hspace{1cm} (11)

Objective functions for the paired etc. comparison lottery error,

\[ (1 - \delta_m) e_+^{cm} + (\delta_m) e_-^{cm} \]  \hspace{1cm} (12)

and constraints similar to (9) and (10) can be established for each combination lottery question, \( m \). For ease of exposition, we do not repeat them here.

**Summary**

The estimation LP is now to minimize the weighted sum of errors, given by equations (LPI), (2), (6), (9), and (12) subject to the constraints of (3), (7), (10), and the mathematical formulation of (11). For example, for the six durable goods in Table 1, there are six reservation price relationships, six probability relationships, five lottery order relationships, and seven combination lottery prize relationships totalling 24 constraints and 24 independent errors in the objective function.
The scaling of the errors varies by the type of relationship, but this is easily reflected in the weights chosen by the analyst. Repeated estimates can be made with alternate weights.

**Example Predictive Test**

Consider the data in Table 1 and suppose we place equal weight on each data type, that is, $W_1 = W_2 = W_3 = W_4$. Applying Eq. (2.3), the parameters from the second (value = 2.5), a television set as her third (value = 3.0), a refrigerator as her first (value = 4.0), and a freezer as her least priority (value = 1.0).

We now compare the budget priority predicted by the estimated model against the observed priorities. As shown in Table 2, the observed budget priorities (row) are not perfectly matched against the model predictions (column). Comparing rank orders implied by the data fitting column of Table 2 to the fourth column we see that the predictions are reasonable but not perfect.
### TABLE 2

<table>
<thead>
<tr>
<th>DURABLE</th>
<th>ESTIMATED UTILITY</th>
<th>UTILITY (\times) PRICE (000's)</th>
<th>ACTUAL BUDGET PRIORITY ORDER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Automobile</td>
<td>10.00</td>
<td>2.0</td>
<td>4</td>
</tr>
<tr>
<td>Furniture</td>
<td>4.00</td>
<td>2.0</td>
<td>3</td>
</tr>
<tr>
<td>Tuition</td>
<td>10.27</td>
<td>5.1</td>
<td>2</td>
</tr>
<tr>
<td>Movie Camera</td>
<td>1.22</td>
<td>2.5</td>
<td>1</td>
</tr>
<tr>
<td>Vacation</td>
<td>1.50</td>
<td>1.5</td>
<td>6</td>
</tr>
<tr>
<td>Freezer</td>
<td>0.30</td>
<td>1.0</td>
<td>5</td>
</tr>
</tbody>
</table>

**CORRELATION OF ESTIMATE WITH BUDGET PRIORITY**

Spearman \(\rho = .87\)

Kendall \(\tau = .69\)

Tuition and the movie camera are predicted and observed to be the top two items, but estimated "value" predicts tuition as the top priority while the consumer feels that the movie camera is her top priority. Overall, the Spearman rank order correlation of the predicted rank from utility per dollar (column 3) and the actual rank (column 4) is .87, while the Kendall rank order correlation is .69.

However, equally weighting of the data types is not the only choice. For example, Table 3 indicates the results we obtained by using each data source separately. For this consumer, it appears that the purchase probabilities, lottery orders, and paired lottery prizes each, alone, provide reasonable estimates of budget priorities; however, in this case, reservation prices do not appear to be as good data as the other measures. In fact, if we drop reservation prices and use equal weights on the other three data sources, we get a higher rank order correlation, .93, than if we use all four data sources.

**VARIATION ACROSS INDIVIDUALS**

At this point in time, efficient computer software for convergent LP estimation is still being developed. In developing this software, we selected a sample of twenty-three budgets with which to test our estimation procedure. The software development and the analysis of the full data set are expected to be completed by the end of 1984.

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5We report only the Spearman correlation for ease of exposition. Results are similar with Kendall's \(\tau\).
Table 3. Varying Weights on Types of Input Data

| Equal Weights to All Four Types             | .87 |
| Reservation Price Weighted Heavily         | .31 |
| Lottery Order Weighted Heavily             | .82 |
| Paired Lottery Prices Weighted Heavily     | .87 |

*"Weighted heavily" means the relevant weight is 100 times more than others.

Figure 1 reports the Spearman correlations of the predicted and actual budgets when the "utilities" are estimated placing equal weights on the four data sources. Overall, the value-priority algorithms do well. For over one-third of the budgets, correlations are .50 or better and the overall critical value that can be applied to Figure 1 is .10. There is no single overall critical value that can be applied to Figure 1.
Variation Across Alternative Weightings of Data Types

By varying \( W_1, W_2, W_3, \) and \( W_4 \) in LP1, we can place differential emphasis on the four data types. For example, if we make \( W_1 \) much larger than \( W_2, W_3, \) and \( W_4, \) we emphasize reservation prices as the primary data source. The results of emphasizing reservation prices are shown in Figure 2a. Overall, reservation prices do about as well as equal weighting of all data sources. For some people, they do very well (correlation = .75 to 1.0).

Figure 2 also gives the results for emphasizing data on purchase probabilities, lottery orders, and combination lottery prizes. From this initial small subsample, it appears that probabilities do best overall; however, we hesitate to generalize until the full sample has been analyzed.

Finally, we can ask the question: "What if we had known a priori which data source was best for each consumer?" If we had known data quality a priori, we would have chosen to emphasize the best data type in our estimation and we would have selected the weights accordingly. Figure 3 displays the results we would have obtained from the best weighting. In this case, 20 of the 23 comparisons, would have had positive correlations and 15 of the 23 comparisons would have had correlations of .50 or better. This is higher than the separate or equally weighted values in Figure 2.

Figure 3 is more like a test of the model's fit to the data than a true predictive test because we used the dependent measure to select the best weighting of data types. But even interpreted as a fit measure, it does suggest strongly that the value priority algorithm is a reasonable explanation of observed budget priorities and the best utility measure may vary by individual.

Managerial Insights

The value priority algorithm is a model of how consumers allocate their budgets to durable goods. It is also interesting to review some insights on which durable goods are given priority in consumer budgets. This information is valuable to managers planning strategies for new automobile models because it indicates which durable goods are likely to compete with automobiles for a share of the consumers' budgets.

The first summary measure is the average lottery prize rank (utility rank not considering price) of a durable when it is in the budget. As indicated in Table 4, the automobile is alive and well as a durable good. On average it was the second highest ranked good with an average rank of 1.33. Houses were the highest ranked and ranks 3 through 6 had something to do with recreation.

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6To avoid trivial solutions to LP1, we require that either \( W_1 \) or \( W_2 \) is non-zero.

7Three budgets have negative correlations in Figure 3 vs. two in Figure 2b because, to date, we have analyzed only 20 of the 23 budgets for the weighting emphasizing purchase probabilities.
Table 4 gives utility rank. But, the value priority algorithm suggests the value, i.e., utility/dollar, is the appropriate comparison measure. Table lists those items that were ranked over automobiles when both an automobile and that item was in the three year (1983, 84, 85) budget plan. For example, when both an automobile and 1983 school tuition were in a budget plan, 1983
The value-proprietary model appears to be a reasonable approach as a model of consumer demand and product behavior. This paper describes the first detailed analysis of the value-proposition.

**SAVINGS AND PRIORITIZATION**

<table>
<thead>
<tr>
<th>Week</th>
<th>Vacation 1985</th>
<th>7.4%</th>
<th>6.2%</th>
<th>Vacation 1989</th>
<th>5.2%</th>
<th>3.6%</th>
<th>2.4%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td>6.2%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>6.4%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>School Tuition 1992</td>
<td>7.4%</td>
<td>7.4%</td>
<td>School Tuition 1992</td>
<td>7.4%</td>
<td>7.4%</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Home Improvement (Major)</td>
<td>7.4%</td>
<td>7.4%</td>
<td>Home Improvement (Minor)</td>
<td>7.4%</td>
<td>7.4%</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Home Repair</td>
<td>7.4%</td>
<td>7.4%</td>
<td>Home Repair</td>
<td>7.4%</td>
<td>7.4%</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>1983 &amp; 1993</td>
<td>7.4%</td>
<td>7.4%</td>
<td>1983 &amp; 1993</td>
<td>7.4%</td>
<td>7.4%</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Vacation 1993</td>
<td>7.4%</td>
<td>7.4%</td>
<td>Vacation 1993</td>
<td>7.4%</td>
<td>7.4%</td>
<td></td>
</tr>
</tbody>
</table>

**PERCENT DISTRIBUTION**

<table>
<thead>
<tr>
<th>Week</th>
<th>Vacation 1985</th>
<th>7.4%</th>
<th>6.2%</th>
<th>Vacation 1989</th>
<th>5.2%</th>
<th>3.6%</th>
<th>2.4%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td>6.2%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>6.4%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>School Tuition 1992</td>
<td>7.4%</td>
<td>7.4%</td>
<td>School Tuition 1992</td>
<td>7.4%</td>
<td>7.4%</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Home Improvement (Major)</td>
<td>7.4%</td>
<td>7.4%</td>
<td>Home Improvement (Minor)</td>
<td>7.4%</td>
<td>7.4%</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Home Repair</td>
<td>7.4%</td>
<td>7.4%</td>
<td>Home Repair</td>
<td>7.4%</td>
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<td>6</td>
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<td>7</td>
<td>Vacation 1993</td>
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**DIAGRAM**

- Differential interaction between end-user and manufacturer.
- Improvement in production would be reflected in increased utility values.
- New products in existing classes could increase utilities for these classes.
- Estimation of utility provided by new products and new classes.
- Consumer surplus.
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- consumers vary in their ability to answer specific question types, but convergent LP estimation can be used to explore this phenomenon and identify the best question type for each consumer; and,

- value priorities provide useful strategic information for durable goods manufacturers.

Based on our experience to date, we believe that the value-priority model and convergent LP estimation provide a number of opportunities for scientifically interesting and managerially relevant research. Among our research priorities are:

- analysis with the full data set;
- a priori identification of which data to rely upon for each individual consumer;
- extension of the empirical analysis to the multi-period theory with interest, borrowing, and depreciation;
- validation via followup interviews to determine what goods the interviewed consumers actually purchased in 1983; and,
- incorporation of the value-priority analyses in the full prelaunch forecasting system for new consumer durables.

We encourage other researchers to join us by taking up the challenge of analyzing consumers' budget allocations.  

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REFERENCES


