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# An Evaluation Cost Model of Consideration Sets

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If utility (net of price) varies by consumption occasion, the consideration set of a rational consumer will represent trade-offs between decision costs and the incremental benefits of choosing from a larger set of brands. If evaluating a brand decreases biases and uncertainty in perceived utility, the decision to evaluate a brand for inclusion in a consideration set is different from the decision to consider an evaluated brand. The decision to consume is, in turn, different from the decision to consider. This article provides analytical expressions for these decision criteria and presents four aggregate implications of the model: (1) distributions of consideration set sizes, (2) order-at-entry penalties, (3) dynamic advertising response, and (4) competitive promotion intensity.

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Since the introduction of the concept of an evoked set by Howard and Sheth (1969), the concept of a set of considered brands has proven valuable in models of consumer response and has elicited a number of experimental studies.

The basic idea is that when choosing to make a purchase, consumers use at least a two-stage process. That is, consumers faced with a large number of brands use a simple heuristic to screen the brands to a relevant set called the consideration set (Alba and Chattopadhyay 1985). Purchase or consumption decisions are then made from brands in this set (see hypotheses in Belonax and Mittelstaedt 1978; Howard and Sheth 1969; Parkinson and Reilly 1979; see also a related discussion in Wright 1975).

There have been many elaborations of the details of the process and much discussion of the appropriate definition of the concept. For our purposes, we are most concerned that at any given consumption occasion consumers do not consider all of the brands available (e.g., there are more than 30 shampoos and more than 160 autos available), but rather consider seriously a much smaller set—a median of four shampoos (Urban 1975) or two to five autos (Grønhaug 1973/ 1974; Hauser, Urban, and Roberts 1983; Ostlund 1973).

The purpose of the present research is to develop a model in which a rational, utility-maximizing consumer finds it optimal to behave in a way consistent with the construct of a consideration set that might contain more than one brand. From a theoretical perspective, such a model is attractive because it is consistent with existing bodies of literature in economics and consumer behavior, is parsimonious and easy to elaborate, and generates interesting hypotheses.

We do not wish to claim that our simple theory can explain all data in the area. We examine only a few aggregate implications of our individual-level model. In particular, we develop its implications for the distribution of decision costs, the rewards to pioneering brands, the dynamics of advertising response, and competitive pricing and promotion decisions. We examine these implications with published data and/or publicly available data bases.

## THE CONSIDERATION SET PHENOMENON

The theoretical construct of a consideration set is those brands that the consumer considers seriously when making a purchase and/or consumption decision. Empirically, quite a few definitions of evoked sets, relevant sets, and consideration sets have been used. For example, Alba and Chattopadhyay (1985), Howard and Sheth (1969), Parkinson and Reilly (1979), and Silk and Urban (1978) each use different operational definitions and different terms. (See Brown and Wildt 1987 for a comparison of five operational definitions.) But whatever the empirical definition, the size of the consideration set tends to be small relative to the total number of brands that could be evaluated. For example, the Exhibit lists the mean or median consideration set sizes from published studies and from the Assessor database.[1] The number of brands available is in the range of 6 to 47.

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[1] Assessor is a pre-test market forecasting system for new products. See Silk and Urban (1978). The Assessor database contains key variables from many of the more than 1,000 Assessor applications. Details are available from Steven Gaskin , M/A/R/C, Inc., 1601 Trapelo Road, Waltham, MA 02154.

**EXHIBIT**

CONSIDERATION SET SIZES FROM PUBLISHED STUDIES AND FROM ASSESSOR DATABASE

| Published studies | | Assessor database[j] | |
|---|---|---|---|
| Category | Mean (or median) consideration set size | Category | Mean consideration set size |
| Antacid[a] | 3.0 | Analgesic | 3.5 |
| Autos[b] (USA) | 8.1 | Antacid | 4.4 |
| Autos[c] (Norway) | 2.0 | Air freshener | 2.2 |
| Beer[d] | 3.0 | Bar soap | 3.7 |
| Beer[e] (USA) | 2.6 | Bathroom cleaner | 5.7 |
| Beer[e] (Canada) | 7.0 | Beer | 6.9 |
| Coffee[e] | 3.3 | Bleach | 3.9 |
| Coffee[f] | 4.2 | Chili | 2.6 |
| Deodorant[g] | 3.0 | Coffee | 4.0 |
| Dishwashing liquid[f] | 5.6 | Cookies | 4.9 |
| Fast food restaurant[h] | 5.4 | Deodorant | 3.9 |
| Food product[e] | 2.9 | Frozen dinners | 3.3 |
| Gasoline[h] | 3.0 | Insecticides | 2.7 |
| Laundry detergent[i] | 5.0 | Laundry detergent | 4.8 |
| Margarine[e] | 4.3 | Laxative | 2.8 |
| Over-the-counter-medicine[a] | 3.0 | Peanut butter | 3.3 |
| Pain reliever[a] | 3.0 | Razors | 2.9 |
| Shampoo[a] | 4.0 | Shampoo | 6.1 |
| Skin care product[a] | 5.0 | Shortening | 6.0 |
| Soft drinks[h] | 5.0 | Sinus medicine | 3.6 |
| Table napkins[f] | 5.0 | Soap | 4.8 |
| Tea[d] | 2.6 | Soda | 5.1 |
| Toothpaste[i] | 3.1 | Yogurt | 3.6 |

[a] Median consideration set from Urban (1975)
[b] Median from Hauser, Urban, and Roberts (1983).
[c] Median from Grønhaug (1973/1974).
[d] Average number of brands purchased in one year (1956–1957), from Massy, Frank, and Lodahl (1968).
[e] Average number of brands purchased in two years, from Wierenga (1974).
[f] Mean from Jarvis and Wilcox (1973).
[g] Median from Silk and Urban (1978).
[h] Grand mean from five measures from Brown and Wildt (1987).
[i] Mean from Campbell (1969).
[j] Mean consideration sets from Assessor database. See Silk and Urban (1978) for details on model and measures. Typical sample sizes are 300 to 600 per study. We selected 23 categories for illustration.

The consideration set phenomenon is critical to the predictive ability of quantitative models. Implementors of pre-test forecasting models (Silk and Urban 1978) and defensive strategy models (Hauser and Gaskin 1984) report that the accuracy of the models depends upon the fact that predictions of consumer choice are made within consideration sets. Urban, Johnson, and Hauser (1985) report that information on which brands are considered together provides an accurate representation of market structure. Katahira (1990) develops a multidimensional scaling algorithm that provides more accurate maps by limiting consumer similarity judgments to consideration sets. Louviere (1988) demonstrates that the estimation of multinomial choice models is dependent on correctly specified consideration set sizes.

Hauser (1978) provides one quantitative measure of the importance of the consideration set phenomenon. He uses an information theoretic statistic to parse the explainable uncertainty in a choice model into (1) that due to limiting the model to consideration sets and (2) the incremental uncertainty explainable by a logit model based on constant-sum, paired-comparison preference measures. The consideration sets account for 78 percent of the explainable uncertainty; the logit model accounts for only 22 percent.

The consideration set concept is consistent with a number of theories and results in behavioral science. For example, Wright (1975) argues that consumers attempt to simplify their decision environment; Miller (1956) reports limitations on human abilities to process and store information; Tversky and Kahneman (1974) review a number of heuristics used in place of detailed estimation of probabilities; and Alba and Hutchinson (1987) report several phenomena related to a simplification of choice through consideration sets. Indeed Alba and Hutchinson suggest that the size and complexity of the sets is related to expertise within a category.

In sum, the concept that consideration sets can contain more than one brand, but not necessarily all brands, is real, important to practical applications, and consistent with prevailing views of how consumers process information. However, the view that consumers simplify decisions with consideration sets does not necessarily mean that consumers are lazy or that they are not rational. We attempt to show that such behavior can be explained in the aggregate by consumers' balancing of consumption utility and evaluation cost. However, before we formalize our concepts, we review briefly some existing perspectives from the literature.

## EXISTING PERSPECTIVES IN THE LITERATURE

Our theory is related to work in economics, marketing, and transportation science.

In economics, Stigler (1961) introduced the concept of search costs and showed that the rational consumer would not search all brands in a market. His core concept is that the expected utility of further search decreases as more brands are examined. Because search costs stay constant, there is an optimal number of brands to search. Nelson (1970) refined the theory by postulating that some products cannot be evaluated without consumption. More recently, Wilde (1981) argued that consumption may be the least expensive search mechanism in some situations (see also Gould 1980; Schmalensee 1982; Urbany and Weilbaker 1987). This stream of research predicts that consumers consider only a subset of the available brands. However, once the search is completed, the best brand is identified. For subsequent decisions, the consideration set is but that one brand rather than a few brands as in the Exhibit.

Marketers have focused on similar issues, but have stressed the information processing components of search costs. Belonax and Mittelstaedt (1978) show that larger evaluation costs (more choice criteria, more ratings variability) lead to smaller consideration sets. Shugan (1980) proposes a "cost of thinking," and Alba and Hutchinson (1987, p. 418) argue that analytical processing can be energy taxing (see also Roberts 1988).

Two interesting theories have been proposed in transportation science. Meyer (1979) allows that consumers learn from consumption, but suggests that different brands have different relative utility on different purchase occasions. This heterogeneity generates brand switching over time and thus learning about several brands. Richardson (1982) extends concepts similar to Stigler's by postulating that consumers update their beliefs as the search proceeds.

However, the emphasis of the marketing and the transportation models has been on which brands are considered for choice rather than which brands are considered on an ongoing basis. The choice of a portfolio of products is usually explained by the concept of variety seeking.

In this section, we build upon the work in economics, marketing, and transportation science by modifying search theory to include variation in utility at different consumption occasions and uncertainty due to lack of knowledge on the part of the consumer. These modifications lead to a model that preserves consideration set sizes with more than one brand but fewer than the total number of brands available.

Our perspective is similar to what Payne (1982) calls the cost/benefit framework, a theoretical framework which postulates that consumers select decision rules after weighing the effort (cost) and accuracy (benefit) of the decision rule. Payne contrasts this framework to the perceptual view, which traces decision rules to basic principles governing human perception, and the production systems view, which focuses on rule-based theories.

Our aggregate focus does not need to make sharp distinctions among the three frameworks. We fully expect that there are complex perceptual processes, such as memory and accessibility, involved in the formation of consideration sets. However, we posit that a rational, cost/benefit approach provides a reasonable explanation of the result of the micro-processes. We believe that the "signal," the rational explanation, will be discernable at the aggregate level over the "noise," the heterogeneous and complex micro-processes.

This perspective is consistent with the notion that consumers try to be rational and, on average, succeed well enough to make a reasonable approximation of cost versus benefit. Perhaps through culture or evolution, modern consumers have developed behavior rules, perhaps even "production systems," that, on average, mimic rationality. For example, Hauser and Urban (1986) show that a simple, naive, consumer-budgeting rule approximates a complex integer programming optimization. Predictions from that simple rule correlated highly with observed consumer budget plans.

A rational model becomes a base against which deviations can be interpreted. For example, the implications of Kahneman and Tversky's (1979) prospect theory are appreciated best when compared to implications of Von Neumann-Morgenstern's utility maximization. A rational model also acts as a bridge by which mathematical theorists and information processing theorists can communicate.

## EVALUATION COST MODEL

We now formalize our concept mathematically and derive the consideration set phenomenon. In later sections, we develop implications that attempt to explain aggregate data. For the following derivation, we assume that we are focusing on a grouping of brands such as might be defined by a market structure analysis (Day et al. 1979; Fraser and Bradford 1983; Srivastava, Leone, and Shocker 1981; Urban et al. 1985). For simplicity, we think of utility as normalized

net of price.

## The Utility of a Brand

Because of the consumer's lack of knowledge and because of variation among consumption occasions, utility is defined as a random variable prior to evaluation. For example, consider a consumer purchasing wine. Before evaluating the wine, the consumer has some expectations of the utility of the wine (e.g., it's red, it's from France), but does not have complete knowledge of its utility. Prior to evaluation, define $\tilde{u}'_{jt}$ as a random variable indicating what the consumer believes his/her utility will be. The consumer recognizes that utility may vary by consumption occasion. Let $\nu_j$ be the mean of that belief. That is,

$$\nu_j = E'(\tilde{u}'_{jt}), \qquad \textbf{(1)}$$

where $E'(\cdot)$ denotes the mathematical expected value operator for utility prior to evaluation. Let $\sigma_u^2$ be the variance of utility prior to consumption.

After evaluation, the consumer learns some aspects of the brand and, perhaps, updates his/her beliefs about utility. For example, our consumer might taste the wine or get a recommendation from an expert. Let $a_j$ be the change in mean value of the consumer's utility due to evaluation, that is,

$$a_j = E(\tilde{u}'_{jt}) - E'(\tilde{u}'_{jt}), \qquad \textbf{(2)}$$

where $E(\cdot)$ denotes the mathematical expected value operator for utility after evaluation and $\tilde{u}'_{jt}$ denotes the post-evaluation utility. Note that $a_j$ can be positive, negative, or zero depending upon whether the consumer's expectation of utility increases, decreases, or remains the same following evaluation.

After evaluation, there is still uncertainty in utility due to variation among consumption occasions. At any given consumption occasion (after evaluation), the consumer can determine with near certainty the utility of the brand. For example, even after the consumer evaluates a wine, its utility will vary depending upon the meal, the guests, the weather, and, perhaps, the consumer's mood. If the consumer buys the wine for a future meal, its appropriateness is uncertain, but the consumer can make a better estimate of its utility for that occasion just before consumption.

Let a random variable, $\tilde{c}_{jt}$, denote the variation in utility due to consumption occasion. That is,

$$\tilde{c}_{jt} = \tilde{u}_{jt} - E(\tilde{u}_{jt}). \qquad \textbf{(3)}$$

Let $\sigma_c^2$ denote the variance in utility from consumption occasion to consumption occasion. Naturally, we assume that the evaluation process reduces the consumer's perception of the uncertainty of utility, hence $\sigma_c^2$ is less than $\sigma_u^2$. For reference, define $\sigma_a^2$ as the amount of variance that was reduced by evaluation.

In this formulation, we assume only that the consumer determines or intuits the utility of the brand. The consumer does this before evaluation, after evaluation (before consumption), and at each consumption occasion. The breakdown of that utility into its components is for the purpose of analysis. The consumer need not distinguish $\nu_j$, $a_j$, or $\tilde{c}_{jt}$. We make this explicit by formulating the theory (Equations 4 through 8) in terms of $\tilde{u}'_{jt}$, and $\tilde{u}_{jt}$ rather than $\nu_j$, $\alpha_j$, or $\tilde{c}_{jt}$. The component definitions are used to simplify the interpretation of the theory and for the mathematical derivations in the Appendix. By definition, only brands that have been evaluated can be in the consideration set, although not all such brands are. Evaluation may or may not require purchase.

On the cost side, we posit a decision cost, $d_j$, of considering a brand at any given purchase occasion. This cost includes the "cost of thinking" to evaluate the considered brands for that purchase occasion as well as any minor search costs, such as reading ingredients. It might also include storage costs. We also posit a search cost, $s_j$, of evaluating a brand for inclusion in the consideration set. This cost includes thinking costs, search costs, and any opportunity loss (Schmalensee 1982) incurred in the evaluation. Although the theory is formulated more generally, it is useful to think of $d_j$ as information processing costs and $s_j$ as information gathering costs. We expect the evaluative search cost, $s_j$, to be larger than the decision cost, $d_j$, but for our theory we need only that both be positive.

Consider a particular purchase occasion for a consumer who considers $n$ brands. Dropping subscripts, $t$, the expected utility of choosing from the consideration set is the expected value of the maximum of $\tilde{u}_1$, $\tilde{u}_2$, …, $\tilde{u}_n$ minus the cost of considering the brands. The expected value of choosing from the consideration set, in symbols, is given by

$$E[\max(\tilde{u}_1, \tilde{u}_2, \ldots, \tilde{u}_n)] - \sum_{j=1}^{n} d_j. \qquad \textbf{(4)}$$

We have assumed that all $n$ brands are considered before a selection is made. We have also assumed that the cost of considering $n$ brands is the sum of the costs for considering each brand.

Equation 4 highlights the reason why we restrict our analysis to a grouping of brands such as might be defined by a

market structure analysis. The first term, the expected value of the maximum of $n$ utilities, assumes that the consumer is choosing one brand rather than a complementary pair. The second term, the cost of deciding among brands, assumes that interactions among the decision costs are negligible—that processing information about one brand in the consideration set does not make processing information about another brand either easier or more difficult. Naturally, future models may wish to investigate these assumptions.

## Decisions to Add or Drop a Considered Brand and to Evaluate Brands

Consider two decisions—the decision to evaluate a brand and the decision to add a brand to the consideration set after it has been evaluated. The decision to evaluate entails a trade-off between the cost of evaluative search and the expected incremental benefits of including a brand in the consideration set for all subsequent purchases. The decision to include a brand after evaluation entails a trade-off between the incremental benefits expected at each consumption occasion and the expected incremental decision costs.

For the decision to add an evaluated brand to the consideration set, the evaluative search cost can be considered a sunk cost. The brand will be added to the consideration set if its expected incremental value for consumption occasions exceeds the cost of deciding among considered brands at consumption occasions. That is, it will be added if the expected utility of choosing from $n$ + 1 brands minus the expected utility of choosing from $n$ brands exceeds the additional cost of evaluating the $n$ + first brand. In symbols,

$$E[\max\{\tilde{u}_1, \tilde{u}_2, \ldots, \tilde{u}_n, \tilde{u}_{n+1}\}] - E[\max\{\tilde{u}_1, \tilde{u}_2, \ldots\ldots, \tilde{u}_n\}] - d_{n+1} > 0. \quad \textbf{(5)}$$

Note that Equation 5 refers to an already evaluated brand. If more than one brand is evaluated simultaneously, the brand with the largest net benefit (the left-hand side of Equation 5) will be added first. Subsequent brands will be added if the equation is still satisfied. Further, several unevaluated brands might satisfy Equation 5, but the consumer will not know this until s/he evaluates those brands.

Note also that Equation 5 implies that a brand might be added to the consideration set even if its expected utility is less than $E[\max\{\tilde{u}_1, \tilde{u}_2, \ldots, \tilde{u}_n\}]$. High variance ($\sigma_c^2$) brands may have high utility for some consumption occasions but low overall utility. They will be added to the consideration set for consumption on those occasions if Equation 5 is satisfied.

For example, Retsina (a Greek wine with a resin taste) might be in a consideration set because it is best for certain occasions (Greek guests and Greek dishes), even though it would not be drunk on most consumption occasions. Whether it is in the consumer's active consideration set depends upon whether the cost of considering it for all consumption occasions (e.g., having it in the wine cellar) exceeds the expected increment in utility of being able to use it for certain occasions. Naturally, this will depend upon how often the consumer has Greek guests and Greek food and on the incremental value (on those occasions) of having Retsina rather than the next best wine in the consideration set.

Arguments similar to those that led to Equation 5 give the condition for dropping a brand from a consideration set. If the distribution of the utility of the $n$th brand changes, perhaps due to a change in the consumer's needs, a change in the product, or a change in advertising, then its contribution to the expected value can decrease to the point where it will drop out. That is, if

$$E[\max\{\tilde{u}_1, \tilde{u}_2, \ldots, \tilde{u}_n\}] - E[\max\{\tilde{u}_1, \tilde{u}_2, \ldots, \tilde{u}_{n-1}\}] - d_n < 0. \quad \textbf{(6)}$$

Finally, if a brand is to be evaluated, a consumer must believe that the expected benefit of considering $n$ + 1 brands will exceed the expected benefit of considering $n$ brands and that it will do so by more than the discounted evaluation search cost. That is,

$$(E'[\max\{\tilde{u}_1, \tilde{u}_2, \ldots, \tilde{u}_n, \tilde{u}_{n+1}\}] - \textstyle\sum_{j=1}^{n+1} d_j)/\gamma - (E[\max\{\tilde{u}_1, \tilde{u}_2, \ldots, \tilde{u}_n\}] - \textstyle\sum_{j=1}^{n} d_j)/\gamma > s_{n+1}, \quad \textbf{(7)}$$

where the (') indicates that the $n$ + first brand has not yet been evaluated. The discount factor, $\gamma$, reflects the fact that the evaluative search cost is "paid" once, while the expected benefits represent an ongoing stream that must be summed and discounted ($\gamma$ > 1). Under specihc assumptions (e.g., Nelson 1970, p. 314), one can calculate $\gamma$ from discount rates and consumption intervals. For our purposes, we need only that the search costs are somehow spread out over the consumption occasions. We rearrange terms in Equation 7, define $F_n = E[\max\{\tilde{u}_1, \tilde{u}_2, \ldots, \tilde{u}_n\}]$, and define $F'_{n+1} = E'[\max\{\tilde{u}_1, \tilde{u}_2, \ldots, \tilde{u}'_{n+1}\}]$ to obtain

$$F'_{n+1} - F_n - \gamma s_{n+1} - d_{n+1} > 0. \quad \textbf{(8)}$$

Note that the process in Equations 5 through 8 is not a static process. For example, advertising, product improvements, or other marketing actions can affect $d_j$, $s_j$, or utility ($\tilde{u}_n$ or $\tilde{u}'_n$). As these variables change, the conditions of Equations 5, 6, and 8 change. The consumer will add brands, drop brands, and/or evaluate brands, which will cause the consideration set to evolve.

## Pre-evaluation Search

Our theory describes how consumers decide to evaluate brands and how they decide to add or subtract brands to or from their consideration sets. It is mute on how they form beliefs about the means and variances of pre- and post-evaluation utility and mute on how they perform the calculations in Equations 5, 6, and 8. Neither of these issues is central to this article, but both issues are important to the study of consumer behavior and will become important if other researchers attempt to elaborate the theory.

Our hypothesis is that, prior to detailed evaluation, consumers use informal, heuristic methods to gather information on perceived means and variances of utility. For example, our consumer might have heard that Napa Valley white wines are good with Boston scrod or have read in *Business Week* (5/15/89, p. 157) that some excellent dessert wines come from the Finger Lakes region of New York. Our consumer might have been impressed by the elegance of the aria, *O mio babbino caro*, in a Tott's Champagne commercial and, hence, might evaluate that champagne for entertaining an important guest. We posit that these methods have decision costs that are well under the more formal evaluative search costs. Certainly the references cited earlier support the hypothesis of informal, heuristic pre-evaluation search.

Finally, let us repeat that we do not hypothesize that consumers are calculating the mathematical integrals implied by the probabilistic expectations in Equations 5, 6, and 8. Such calculations are difficult even for trained mathematicians. We hypothesize only that the calculations are a reasonable representation of the results of individual-specific and situation-specific judgments. Such individual judgments could well have perceptual and/or production system components. However, at an aggregate level, individual differences in behavior are considered noise for the purposes of this analysis, and we posit that Equations 5, 6, and 8 describe consumers' actions.

## Fixed Sample Versus Sequential Samples

Implicit in our derivation is the assumption that the two phases of consumer behavior, consideration and consumption, are approached differently. Equation 4 implies that once a consideration set is formed, the consumer makes a consumption decision with a fixed sample search. (S/he knows the number of brands, $n$, to be searched and "searches" all of them, incurring the decision costs, $d_j$, for all $n$ brands.)

The decision to add to the consideration set is a sequential sampling strategy. Brands are evaluated in some order determined by pre-evaluation. Equations 5, 6, and 8 are applied sequentially, with brands being added or dropped depending upon incremental costs and benefits.

This two-phase strategy makes our model a mixed sampling model. We posit that it is a reasonable representation of aggregate consumer behavior. At this time, we do not have any empirical evidence to support this proposition.

Note that the sequential nature of the consideration decision and the heuristic nature of pre-evaluative search add a certain randomness to our model. For example, brands evaluated first have a greater chance of being in the consideration set. (The advantages of a brand's being evaluated first are the focus of our second aggregate implication.)

We now interpret the plausibility of the implications of Equations 5, 6, and 8. We then demonstrate four aggregate implications of the mathematical theory consistent with aggregate data.

## Implications at the Level of the Individual Consumer

Suppose that we are in an ideal experimental situation where we can vary one parameter, say decision costs, while holding all else equal. Then Equations 5 through 8 imply that:

- consideration sets will be smaller for larger decision costs (larger $d_{n+1}$ in Equation 5 implies fewer brands will be added),
- consideration sets will vary less over time for larger evaluation costs (larger $s_{n+1}$, means the condition of Equation 8 is less likely to be satisfied as $\tilde{u}_{n+1}$ and $d_{n+1}$ vary),
- brands with lower decision costs are more likely to be considered (smaller $d_{n+1}$ in Equation 5 means the add condition is more likely to be satisfied),
- brands with lower evaluation costs are more likely to be considered (smaller $s_{n+1}$ in Equation 8 means the brand is more likely to be evaluated and, if Equation 5 is satisfied, considered),
- consumers with lower decision costs will have larger consideration sets (consumers with smaller $d_{n+1}$ will find more brands satisfying Equation 5),
- consumers with lower evaluation costs will have consideration sets that change more often (similar argument applied to Equation 8),

- greater variance over consumption occasions implies larger consideration sets (larger variances, $\sigma_c^2$, imply the expectation in Equation 4 is larger).

We again caution the reader that these predictions are ceteris paribus. For example, if in a real market greater consumption variance is correlated with decision cost, then predictions are ambiguous because the consumption variance may counteract the decision cost.

It is beyond the scope of this article to undertake experiments where each parameter is varied independently. However, we believe that these predictions have face validity subject to future tests. At minimum, the first implication is not inconsistent with the experiments by Belonax and Mittelstaedt (1978), which varied components of decision costs, such as more ratings variability.

## Implications at the Level of the Firm

To sell more items of a brand, a firm will want to influence consumers to evaluate its brand, encourage consumers to add evaluated brands to their consideration sets, and encourage consumers to keep considered brands in their consideration sets. To do this, a firm can influence the means and variances of the perceived utility of its brand,[2] the evaluative search cost, and the ongoing decision cost.

Product improvements affect the post-evaluation mean, $E(\tilde{u}_{jt})$, and the consumption variation, $\sigma_c^2$. Actually, it is not the variance per se that helps a product enter the consideration set but rather the upper part of the distribution. (Recall that Equations 5, 6, and 8 are defined on the maximum of a set of random variables.) Thus, a laundry detergent may be in a consideration set because of its use for delicates even though it is very bad for cottons, or a traveler to Boston might bring a variety of shirts (blouses) because of the unpredictability of the weather.

Advertising communicates. It can increase $E'(\tilde{u}'_{jt})$. The unique selling proposition (e.g., Aaker and Myers 1987) can position a brand for specific consumption occasions and increase the positive aspects of utility for those occasions ($\sigma_c^{2'}$). For image-laden products, such as soft drinks and cosmetics, advertising can actually increase utility (see Levy 1959). Informative advertising decreases the effort of obtaining information ($s_i$). Free samples, coupons, and price-off deals all make the brand easier to try and, for those categories where evaluation includes trying the brand, will decrease the cost of evaluative search ($s_i$).

All of these arguments are intuitive. They do not test our theory, but they do aid our understanding of its implications.

# AGGREGATE ANALYSES

Theories of consumer behavior can be examined in a number of ways. For example, one common means of examining a micro-level theory is to design an experiment to isolate the postulated phenomena and attempt to falsify its predictions. Another approach is to parameterize the hypothesis, estimate the parameters, and use statistical techniques to test the magnitude and/or signs of the parameters. Our approach is aggregate analysis to explain existing data, i.e., published and/or publicly available data. We examine four different aggregate implications of our theory. We feel that each implication is plausible and consistent with the existing data.

[2] Or, more generally, the means plus the distributions of $\tilde{u}'_{jt}$ and $\tilde{u}_{jt}$.

Equations 5, 6, and 8 state the theory in a general form; aggregate analysis requires analytical simplicity. Thus, for each test we make additional assumptions that restrict the theory's generality. If the restricted model explains the aggregate data, then we have demonstrated a case where the data is consistent with the less restricted, general model. (Of course, there might be another set of restrictions that also explains the data.) Note that by this line of reasoning the restrictions need not be the same for each test, as long as they do not contradict one another.

It is the nature of aggregate analysis that we cannot observe the micro-processes. Thus, for any given aggregate implication, there may be rival hypotheses that explain the data and that do not contradict one another. If such hypotheses are generated then, perhaps, future experiments can be designed to distinguish between the set of rival hypotheses and our theory.

**TABLE 1**

COMPARISON OF CONSIDERATION SET FREQUENCIES AND PREDICTIONS OF EVALUATION COST MODEL

| | Percent who consider n products[a] | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Deodorants (Silk and Urban 1978) | | Plastic wrap (Hauser and Gaskin 1984) | | Laundry detergents (Campbell 1969) | | Refrigerated juices Assessor database | |
| Number of products And fit statistics | Actual | Predicted | Actual | Predicted | Actual | Predicted | Actual | Predicted |
| n=1 | - | - | - | - | 7.4 | 9.6 | 4.6 | 3.5 |
| n=2 | 31.8 | 31.2 | 16.0 | 15.8 | 14.3 | 15.2 | 27.6 | 27.6 |
| n=3 | 31.8 | 34.1 | 27.9 | 29.8 | 17.5 | 13.7 | 30.0 | 32.1 |
| n=4 | 23.1 | 19.6 | 27.9 | 24.8 | 9.5 | 10.8 | 24.0 | 19.3 |
| n=5 | 7.1 | 9.0 | 17.8 | 15.1 | 10.6 | 9.0 | 9.8 | 9.7 |
| n=6 | 4.0 | 3.7 | 7.4 | 7.5 | 9.0 | 6.8 | 2.8 | 3.6 |
| n=7 | 2.3 | 2.4 | 3.0 | 3.2 | 31.7[b] | 34.6 | 1.6 | 3.6 |
| Chi-squared[c] | 3.64 | | 3.00 | | 5.86 | | 10.09 | |
| Sample size | 299 | | 298 | | 187 | | 346 | |
| Degrees of freedom | 5 | | 5 | | 6 | | 6 | |
| μ | 0.25 | | 0.195 | | 0.25 | | 0.25 | |
| Σ | 0.13 | | 0.10 | | 0.40 | | 0.14 | |

[a] Percent who consider 1 and 2 reported under n = 2.

[b] Truncated at n ≤ 7 for comparison. For more detail on n > 7, see Figure A.

[c] Critical values for 0.05 level: 11.07 for 5 degrees of freedom, 12.59 for 6 degrees of freedom.

# AGGREGATE IMPLICATIONS

## Distribution of Decision Costs

If for all brands we knew the evaluative search costs and the distribution of pre-evaluation utility, we could predict which brands would be considered. Alternatively, if we knew the decision costs and the distribution of post-evaluation utility and if they did not vary by brand, we could use Equation 5 to predict the number of brands the consumer would consider.

To predict the distribution of consideration set sizes across consumers, the model needs two additional inputs. We need to know the distribution of the post-evaluation utilities across brands and the distribution of decision costs across consumers.

For the purpose of this analysis, we sacrifice differences among the means of the pre-evaluation utilities, $E'(\tilde{u}'_{jt})$, and assume that the post-evaluation utilities are independent across $j$ and that they are distributed as normal random variables with the same means and variances. Because this i.i.d. assumption (independent and identically distributed random variables) blurs pre-evaluation differences among brands, it will make it difficult to determine which brands are to be in the consideration set, but it enables us to determine how many brands will be in the consideration set.

In the Appendix, we show that under this assumption Equation 5 reduces to Equation 9:

$$\Delta e_n > d/\sigma_c, \qquad \textbf{(9)}$$

where $\Delta e_n$ is a tabled function (see the Appendix) representing the increment in the expected value of the maximum of $n$+1 rather than $n$ standardized normal random variables. The decision cost, $d$, and the standard deviation of consumption utility, $\sigma_c$, are no longer subscripted by $j$ due to the i.i.d. assumption.

Naturally, we do not expect consumers to be equal in their decision costs or their perceptions of the variation in utility. That is, if $\lambda = d/\sigma_c$, we expect $\lambda$ to vary across consumers. We have no proven theory to predict the distribution of

λ, but the lognormal distribution is one reasonable candidate. For example, many empirical cost distributions are lognormally distributed, and Ijiri and Simon (1967) demonstrate that natural learning processes converge to lognormal distributions as their number grows.

If we assume that λ is lognormally distributed with mean, $\mu$, and variance, Σ, then the probability that a consumer considers $n$ brands, $P_n$, is given by

$$P_n = \Lambda(\Delta e_{n-1} \mid \mu, \Sigma) - \Lambda(\Delta e_n \mid \mu, \Sigma), \qquad \textbf{(10)}$$

where $\Lambda(\cdot|\mu, \Sigma)$ is a cumulative lognormal distribution.

Given a distribution of consideration set frequencies, Equation 9 implies a histogram for λ. We examined data from Campbell (1969) for laundry detergents, from Silk and Urban (1978) for deodorants, from the Hauser and Gaskin (1984) database for plastic wraps, and from the Assessor database for refrigerated juices. The data and lognormal fits are given in Table 1 and plotted in Figure A.

Since the empirical data can take on any shape, even multimodal, the "lognormalness" of the histograms in Figure A is encouraging. In all four cases, a contingency test between predicted and observed frequencies does not reject the fit at the 0.05 level. Other distributions, such as the normal distribution and the uniform distribution, do not fit the data nearly as well (see Table 1).

Naturally, a lognormal distribution may not describe all of the phenomena in consideration-set frequency data. For example, in some Assessor studies, the sample sizes are quite large (900+); the histograms look lognormal, but do not pass the chi-squared test. Similarly, the model has some trouble with the tails of distributions in categories where many brands are considered. The restricted model of Equation 9 seems to capture the main phenomenon, but would need to be elaborated in some product categories. Perhaps future analytical models of consumer behavior can derive the lognormal distribution from "first principles" rather than simply demonstrating its empirical fit.

## Order-of-Entry Penalties

When a new brand is evaluated (Equation 8) or enters the consideration set (Equation 5), its perceived incremental utility must exceed the discounted evaluative search and/or decision cost. When more brands are in the market, the expected utility of the maximum best brand among considered brands is usually larger; hence, the threshold is larger. Thus, if two brands enter the market with the same distribution of perceived utility, the brand that enters earlier will be considered more often. If it is considered more often, it should have a higher market share.

As before, we assume that the post-evaluation utilities are independent and identically distributed, so the likelihood of the $n$th brand's being considered should be related to $\Delta e_n$. Further, the ratio of shares between the $n$th and the first brand should be a function of the ratio of incremental expected utilities $\Delta e_n/\Delta e_1$. We expect that the ratio of shares will decrease at a slower rate than the ratio of $\Delta e$s will because, at the time the $n$th brand enters, some consumers will have consideration sets of one brand, some of two brands, and so on. The effective utility increment will be a weighted sum of $\Delta e_1$, $\Delta e_2$…, $\Delta e_n$; it will not be $\Delta e_n$. The weights would reflect the number of consumers considering one brand, two brands, …, $n$ brands.

Based on a statistical analysis of 129 brands across 36 categories, Urban et al. (1986) estimated empirical order-of-entry penalties. Because the brands in their sample differed on perceived position and advertising expenditures, the estimation equations included position and advertising as covariates.

From data similar to that in Table 1, we could compute the weights for the $\Delta e$s for specific categories. We do not know which average weights apply to the 36 categories in the Urban et al. analysis. However, from Table 1 we can posit that the weights for $n$ = 2 and $n$ = 3 should be larger than the other weights. One parsimonious assumption is to make the weights for $n$ = 2 and $n$ = 3 equal and larger than the other weights, which are also set equal to one another. Because the weights must add to 100 percent, this gives us one degree of freedom with which to estimate weights to match the Urban et al. estimates. To further avoid over-fitting, we restrict ourselves to percentages of 5 percent, 10 percent, 15 percent, and so on.

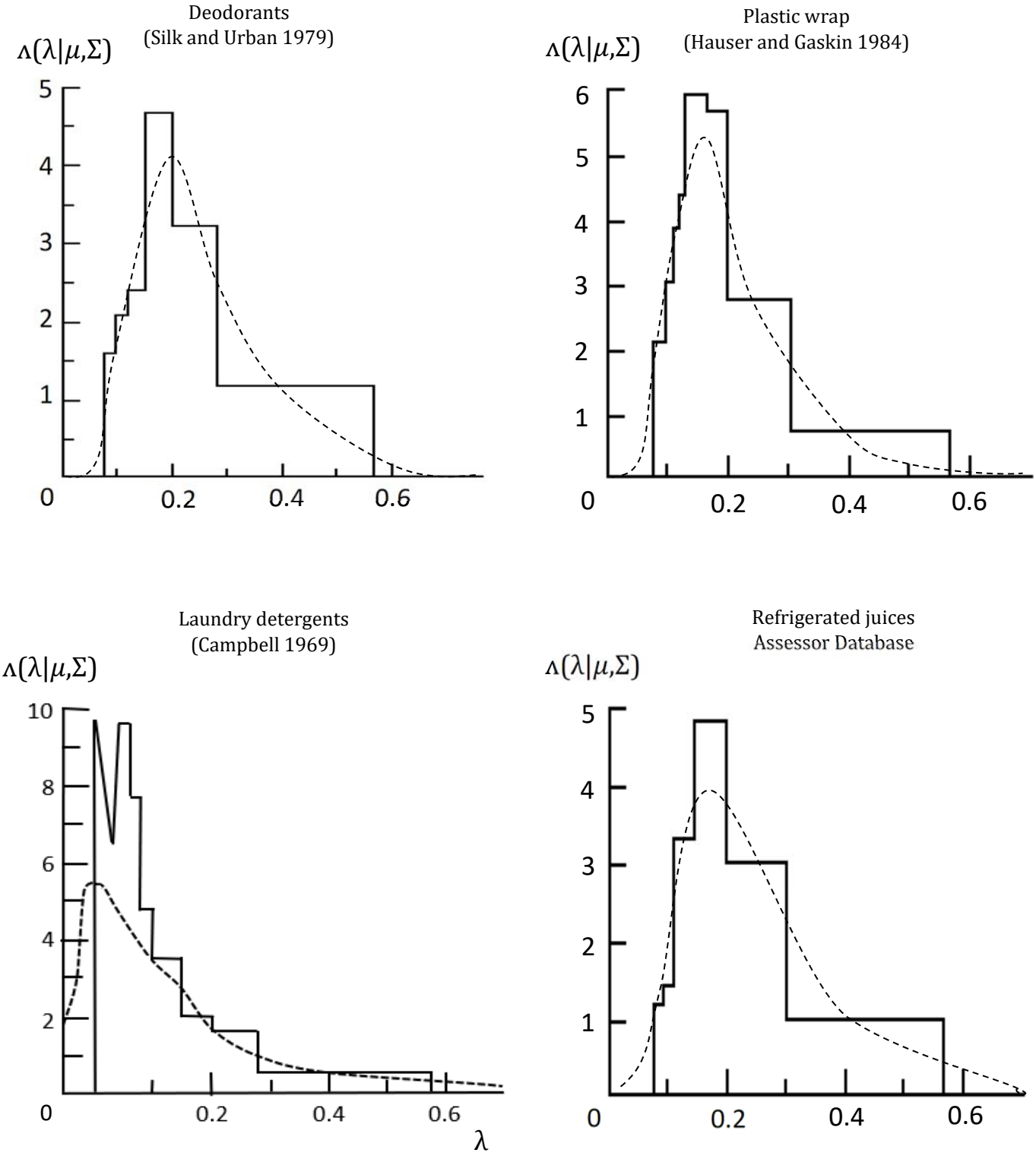
The following tabulation plots the empirical order-of-entry penalties and the weighted sum of the $\Delta e$ ratios (in column 2). The weights of 15 percent, 20 percent, 20 percent, 15 percent, 15 percent, and 15 percent for $n$ = 1 to 6 were determined by minimizing the sum of squared errors; the estimated ratio of the share of the $n$th brand to the first brand is from Urban et al. (1986), and predictions are based on Equation 14 in the Appendix.

| *Order of entry* | *Empirical penalty* | *Prediction* |
|---|---|---|
| 1 | 1.00 | 1.00 |
| 2 | 0.71 | 0.71 |
| 3 | 0.58 | 0.57 |
| 4 | 0.51 | 0.50 |
| 5 | 0.45 | 0.44 |
| 6 | 0.41 | 0.40 |

The close agreement of the empirical penalties with those predicted by our theory is provocative. Clearly, we can be accused of fitting the data, and to some extent that criticism sticks, but we feel that the ease with which we were able to obtain agreement bears further investigation.

**FIGURE A**

HISTOGRAMS OF DECISION COST RATIOS (λ) VERSUS LOGNORMAL DISTRIBUTIONS



## Dynamic Advertising Response

In general, one could argue that advertising may affect all parameters in the model. For some brands, it is reasonable that advertising affects the ongoing components of utility. For example, advertising for Tide may reassure consumers that their clothes are as clean as they can be, that having clean clothes is socially important, and that they will be judged (e.g., at the laundromat, at the grocery store) by the laundry detergents they use. Clearly, advertising also may affect any perceived biases, $a_j$, and any uncertainty (or lack thereof) in perceived utility, $\sigma_a^2$. (Recall that $a_j$ and $\sigma_a^2$ measure the difference between pre- and post-evaluation utility.)

Another way to introduce advertising to the analytical model is through the decision costs, $d_j$, and the evaluative search costs, $s_j$. The assumption that these costs decrease with advertising can be justified by arguments about memory, accessibility, expertise, and so on (Alba and Hutchinson 1987; Miller 1956; Nedungadi and Hutchinson 1985). We now look at the implications of this assumption.

Because $d_j$ and $s_j$ appear in Equations 5, 6, and 8, advertising, and thus changes in these costs, affects the probability that a brand will be added to the consideration set, dropped from the consideration set, or evaluated for potential addition to the consideration set. But advertising will affect each of these probabilities differently.

To illustrate this difference, consider the short-run effects of a decrease in advertising versus an increase in advertising. If we decrease advertising for the *n*th brand, we increase decision costs, $d_n$. This will cause some consumers who now consider the *n*th brand to drop it from their consideration sets. It does not affect those consumers who do not consider the *n*th brand. However, if we increase advertising, we cause some consumers who evaluated the brand at an earlier time to reevaluate it and perhaps add it to their consideration set. The mechanism will be the mirror image of the dropping mechanism and should produce aggregate effects of the same magnitude.

When advertising also affects the evaluative search cost, $s_n$, there is an additional effect—some new consumers will decide to evaluate the brand and some of these will find it sufficiently attractive to add to their consideration set. This effect will be in addition to the effect on decision costs.[3]

Furthermore, the decision to evaluate a brand is based on pre-evaluation utility, which we expect to be more sensitive to advertising than post-evaluation utility. The decision to drop a brand is based only on the less sensitive post-evaluation utility.

Taken together, these arguments imply that the decision to drop a brand from a consideration set should be less responsive to advertising than the decision to add a brand to the consideration set. If sales are dependent upon consideration set membership, then the response to increases in advertising should be larger than the response to decreases in advertising. We show in the Appendix that such magnitude differences will imply that sales will respond more rapidly to advertising increases than to advertising decreases.

One way to examine this hypothesis would be: (1) increase advertising from $\alpha$ to $\alpha + \Delta\alpha$, (2) measure the rate of increase, (3) bring it back to $\alpha$, (4) wait until it stabilizes, (5) decrease advertising from $\alpha$ to $\alpha - \Delta\alpha$, and (6) measure the rate of decrease. Unfortunately, such data are not available.

Alternatively, under mild technical assumptions, we can examine the hypothesis with a typical "heavy-up" advertising experiment.[4] That is, increase advertising from $\alpha$ to $\alpha + \Delta\alpha$ and observe the rate of increase and then decrease advertising from $\alpha + \Delta\alpha$ to $\alpha$ and observe the rate of decrease. Little (1979) reports the results of heavy-up experiments. Although the data are noisy, his interpretation is that the sales response to advertising is much more rapid when advertising is increased than when it is decreased. (Little claims that these data are typical.)

## Competitive Promotion and Price

Intuitively, if there are more brands competing for consumer purchases, the market should be more competitive. In equilibrium, as brands react to one another, this competitiveness should lead to more promotional activity and to smaller margins.

In traditional economic theory, one measure of competitiveness is the number of firms in a market. In information economics (e.g., Nelson 1970), this measure is the average number of brands that consumers search or experience. The evaluation cost model of consideration sets modifies the measure still further. We argue that the appropriate measure is the average number of brands considered.

*Price-Cost Margins*. Assume that all brands are equal in the sense that the ex ante expected valuations are equal. The more brands a consumer considers, the more price sensitive s/he will be. Reacting to this price sensitivity, firms will find it optimal to price lower when consumers consider more brands. In the Appendix, we argue that the percentage markup (price–cost/price) will be proportional to $(1+ \beta_1\bar{C})^{-1}$, where $\beta_1$ is a parameter and $\bar{C}$ is the size of the average

[3] Note that this argument assumes that there are consumers who have not yet evaluated the brand—those consumers new to the market or those who evaluated the brand at some earlier time and have forgotten the details of that evaluation.

[4] In a heavy-up experiment, the decrease starts from a higher level of advertising than does the increase. The technical assumption is that this difference in levels does not have an overwhelming impact on the rates of increase or decrease.

consideration set. In contrast, economists who assume that all brands are considered predict that the percentage markup is proportional to $(1+ \beta_2 N)^{-1}$, where $N$ is the number of brands in the market.

Profit margins for package goods brands are considered highly proprietary. We have not been able to obtain price-cost margins at the same level of aggregation as our data on consideration set sizes.[5] Perhaps future developments will provide data at the proper level of aggregation to examine the relationship between average consideration set sizes and price-cost margins.

*Promotion Intensity*. The analysis with respect to price-cost margins is interesting, but difficult to examine empirically. A related perspective is that promotion intensity is an alternative measure of competitive activity. That is, rather than lower the posted price, brands can raise their level of promotion. If this were true, then in a market that is more competitive, brands will promote more. There are many ways to measure promotion intensity. The measure available to us is the percent of volume sold on promotion. If brands do promote more when the market is more competitive, then our theory predicts that brands promote more when consumers' consideration sets are larger.

We can argue also that greater promotion lowers the average price paid and thus raises the (net) utility in Equation 5. For product categories where evaluation requires trial, promotion lowers the search cost in Equation 8. Thus, our theory also predicts that consumers will consider more brands when brands promote more. At this point, we cannot untangle the skein of causality, but, at minimum, promotion intensity and the average size of the consideration set should be positively correlated.

Information Resources, Inc. (1987) publishes the *Marketing Facebook™*, which provides data by product category on the percent of volume sold on promotion. The data is based on a panel of 30,000 consumers located in 12 geographically dispersed markets, and covers all purchases by panel members in 1986. Promotions include print ad features, in-store displays, shelf price reductions, store coupons, and manufacturer coupons.[6] The average consideration set sizes were obtained from the Assessor database (see Footnote 1).

Table 2 reports the results of the analysis. The correlation between the percent volume on promotion and the average consideration set size is significant at the 0.01 level. The data are plotted in Figure B.

One rival hypothesis, based on traditional economic theory, is that the total number of brands drives promotion intensity and that the average consideration set size is related to the total number of brands. Indeed, the correlation between the consideration set size and the total number of brands is 0.42, which is significant at the 0.05 level.

**TABLE 2**
REGRESSIONS OF PERCENT VOLUME ON PROMOTION
VERSUS CONSIDERATION SET SIZE AND NUMBER
OF BRANDS IN CATEGORY[a]

| Explanatory variables and statistics | Consideration set only | Number of brands only | Consideration plus brands |
|---|---|---|---|
| Consideration set size (t-value) | 3.14 | - | 2.33 |
| Number of brands (t-value) | - | 2.35 | 1.28 |
| Correlation coefficient | 0.50 | 0.39 | 0.54 |
| $R^2$ | 0.25 | 0.15 | 0.29 |
| F-ratio | 9.87 | 5.50 | 5.87 |
| Sum of squared errors[b] | 4,403.1 | 4,945.3 | 4,164.8 |

[a] Comparisons: add consideration set size (column 3) versus (column 2), F = 5.44; add number of brands (column 3) versus (column 1), F = 1.66.

[b] Total sum of squares is 5,851.9. Number of observations is 31.

[5] The only public database is the Census of Manufacturers, which allows one to estimate (Sales—Production Costs)/Sales at the four-digit SIC code level (see Domowitz, Hubbard, and Peterson 1986). By controlling for advertising to sales and assets to sales, Domowitz et al. were able to obtain very aggregate measures of profit margins. We attempted to merge the consideration set data on 31 product categories with the SIC code data. Unfortunately, the four-digit SIC code merges diverse package goods categories. Also, many manufacturers, such as Procter & Gamble, compete in more than one SIC code. The merged data had too few observations and too much noise to examine our hypotheses.

[6] The *Marketing Facebook™* explicitly considers overlap among ad features, displays, shelf price reductions, and store coupons by providing a measure of percent volume on any combination of trade deals. Manufacturer coupons are treated separately. We created a variable—"promotion"—that was the sum of volume on trade deals and on manufacturer coupons. Because this variable does not account for overlap—volume sold via manufacturer coupons and trade deals—we cleared another variable (equal to deal + coupon – deal X coupon), which accounts for the overlap. The results (e.g., Table 2 and Figure B) were similar. All qualitative conclusions were the same.

To examine the rival hypothesis, we obtained the number of brands by counting the brands in the *Marketing Factbook™*. Data is usually reported on brands purchased at least once by at least half of 1 percent of the households in the panel. The analysis is shown in Table 3.

The number of brands is correlated with promotion intensity at the 0.05 level, but the correlation for the number of brands is less than the correlation for the consideration set size. If we examine the nested regression models, a model with the evoked set size and the number of brands explains significantly more than a model based only on the number of brands. However, the number of brands does not add significant explanatory power to a model based on the consideration set size alone.

A more rigorous statistical test of the non-nested hypotheses is the *j*-test of Davidson and MacKinnon (1981). The *j*-test compares two linear bivariate models through the *t*-statistics in a linear model with both independent variables. As reported in the last column in Table 2, the data do not reject the consideration set model because the *t*-statistic on "number of brands" is insignificant.[7] Thus, based on Table 2, we conclude that consideration set size is a better indicator of competitive promotion activity than is the total number of brands.

Table 2 shows that consideration set sizes and promotional intensity are correlated. Neither the regressions nor our theory postulates causality. We are working on a simultaneous-equilibrium model in which firms determine promotion intensity knowing that consumers react via Equations 5 through 8 and select consideration set sizes based on firm behavior.

# DISCUSSION

## Summary

The concept of a consideration set is an important construct in the study of consumer behavior. Over the last 20 years, there has been much written on the consideration set and its implications. In this article, we propose an analytical model based on both variation in utility (net of price per use) across consumption occasions and uncertainty in perceived utility prior to evaluation. By assuming that the consumer balances the benefits between choosing the best product within a consideration set versus the decision cost and/or evaluative search cost, we derive an analytical expression for the conditions of adding or dropping brands from consideration sets and for evaluating brands for inclusion in consideration sets.

We then examine the model's aggregate implications and show that its implications are consistent with published aggregate data on the distribution of consideration set size, rewards to pioneering brands, the dynamics of advertising response, and the relationship between promotion intensity and average consideration set size. Although our theory is consistent with the aggregate data, other models based on perceptual or production system explanations might explain the data as well. We hope that the data themselves encourage further research.

## Generalizations

To keep the exposition transparent, we presented the model in a simple and stylized version. It is a natural task of further research to add more features to the model such that its predictive power and realism can be improved. Several possible generalizations are listed, each of which could be consistent with our model:

1. We formulated decision costs as additive. That is, the cost of evaluating *n* brands is the sum of the decision costs for each brand. Memory constraints (Miller 1956) would imply that decision costs are a convex function of the number of brands in the consideration set. In this case, Equations 5 through 8 get more complicated, but our qualitative results should remain unchanged.

2. Differences in accessibility (Nedungadi and Hutchinson 1985), expertise (Alba and Hutchinson 1987), and forgetfulness imply that the decision costs and the evaluative search costs depend on brand characteristics, advertising, history, and so on. Explicit models might investigate how firms could influence consumers to consider their brands.

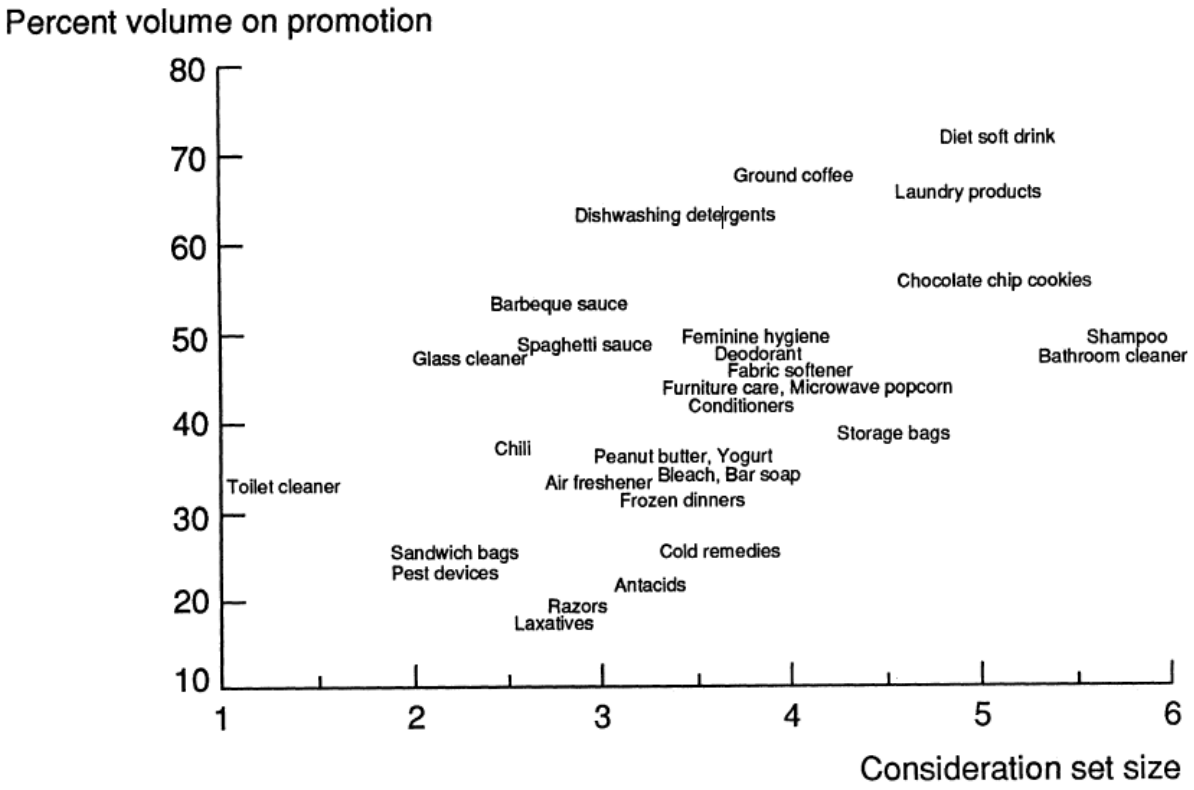
3. The perceptual perspective implies that consumers use heuristics that may or may not approximate Equations 5, 6, and 8. How closely observed heuristics approximate these equations at the level of the individual consumer is an open question. If they do, on average, then we can model utility as revealed with error.

4. We modeled both evaluative search and decision as distinct processes. In principle, one could think of these as consisting of several interrelated steps that are modeled explicitly.

[7] To check the sensitivity of the results to our measure of the number of brands, we reran the analysis with (1) the number of brands with 2 percent or higher market share and (2) a logarithmic transformation of the number of brands. In each case, the $R^2$ measures were slightly lower, but the nested and non-nested model tests gave the same qualitative results.

**FIGURE B**

PERCENT VOLUME ON PROMOTION VERSUS AVERAGE CONSIDERATION SET SIZE




5. In Equations 4 through 8, we model choice within a consideration set as a fixed sample choice and the choice of which brands to consider as a sequential sampling problem. Future research might provide both behavioral and analytical justification (and challenge) to this assumption of a mixed sampling strategy.

6. In general, Equations 5 through 8 can handle interdependencies between the distributions of the $\tilde{u}_{jt}$s, but not easily. When the prior distributions are intercorrelated, we must model the portfolio effect. For one model within the context of consideration sets, see Meyer (1979). See related discussion in Sudharshan, May, and Shocker (1987).

Finally, we recognize that aggregate analyses are but one step in theory development. Other steps include micro-level testing through experiments and/or detailed process measures. Such tests are beyond the scope of this article (and outside our area of expertise) and are left for future work.

## APPENDIX: FORMAL DERIVATIONS

### Distribution of Decision Costs

When the $\tilde{u}_j$ are independent and identically distributed random variables, we can drop the $j$ subscript on $v_j$ and $a_j$, Identical decision costs allow the subscript on $d_j$ to be dropped.

Because the means, $v + a$, and variances, $\sigma_c^2$, are equal over the $\tilde{u}_j$, we transform the calculation of $F_n$ such that $F_n$ equals the mean of the $\tilde{u}_j$ plus $\sigma_c$ times the expected value of the maximum of $n$ standardized random variables. When the distribution of $\tilde{u}_j$ is normal, this maximum is a tabled function called $e_n$. See David (1970, p. 50), Gumbel (1958, p. 131), Gross (1972, p. 92), Stigler (1961, p. 215), and Urban and Hauser (1980, p. 385) for tables of $e_n$. In symbols,

$$F_n = E[\max(\tilde{u}_1, \tilde{u}_2, \ldots, \tilde{u}_n)] = v + a + \sigma_c e_n. \qquad \textbf{(11)}$$

Substituting Equation 11 into Equation 5 yields,

$$v + a + \sigma_c e_{n+1} - (v + a + \sigma_c e_n) - d > 0. \qquad \textbf{(12)}$$

Simplifying Equation 12 yields

$$\Delta e_n = e_{n+1} - e_n = d/\sigma_c . \qquad \textbf{(13)}$$

Finally, Equation 9 is just a statement that consumers with λ between $\Delta e_{n-1}$, and $\Delta e_n$ will consider $n$ brands—the difference in the cumulative density of λ for those two values.

## Order-of-Entry Penalties

Let $\gamma_\ell$ represent the percent of the consumers who consider $\ell$ brands when there are $N$ brands in the market ($\ell$ = 1 to $N$). Assume that when there are fewer than $N$ brands in the market, the relative percentages are proportional to $\gamma_\ell$. Then the average incremental benefit that the $n$th brand must provide to enter and be considered is just the sum of the $\Delta e$s weighted by the $\gamma_\ell$s, where the $\gamma_\ell$s are normalized to add to 1.0. In symbols,

$$\text{average benefit required} = \left(\sum_{\ell=1}^{n} \gamma_\ell \Delta e_n\right)/\left(\sum_{\ell=1}^{n} \gamma_\ell\right). \qquad \textbf{(14)}$$

The order of entry penalty is the Equation 14 divided by $\Delta e_1$.

## Dynamic Advertising Response

In the text, we argued that Equations 4 through 8 imply sales should be more responsive to advertising increases than to advertising decreases. We show here that this implies a more rapid response to increases than to decreases.

Following Little (1979) and Nerlove and Arrow (1962), assume that advertising effects accumulate (perhaps due to memory effects) but that there is some forgetting, so these accumulations must be discounted. Call the net accumulation goodwill, $A$. With these assumptions, if a firm spends at a rate of $\alpha(\tau)$ at time τ, then the goodwill at time $t$ is

$$A(t) = \int_{-\infty}^{t} \alpha(r) e^{-r(t-r)} d\tau. \qquad \textbf{(15)}$$

If we advertise at $\alpha_0$ from t = – ∞ to $t$ = 0 and, at $t$ = 0, raise advertising to $\alpha_0 + \Delta\alpha$, this integration reduces to

$$A(t) = \alpha_0/r + (\Delta\alpha/r)[1 - e^{-rt}] \text{ for } t \geq 0. \qquad \textbf{(16)}$$

Differentiating gives $\partial A/\partial t = \Delta\alpha e^{-rt} > 0$. Since our hypothesis states that $\partial(\text{sales})/\partial A > 0$ and that this partial derivative is larger in magnitude for positive $\Delta\alpha$ than for negative $\Delta\alpha$, the result follows from the chain rule of differentiation.

## Competitive Price Response

Let $\gamma_\ell$ be the fraction of consumers who consider exactly $\ell$ brands. Of these, $f_{j\ell}$ *will* consider brand $j$. Let $S_{j\ell}$ be the sales of brand $j$ if all consumers considered $\ell$ brands and each subset of $\ell$ from $N$ brands was equally likely. Let $p_j$, be brand $j$'s price and $k_j$ be its marginal cost. Then the profit, $\pi_j$, net of fixed costs, will be

$$\pi_j = (p_j - k_j) \sum_{\ell=}^{N} \gamma_\ell f_{j\ell} S_{j\ell} \text{ for } j = 1 \text{ to } N . \qquad \textbf{(17)}$$

If each firm takes the others as given, then the first order conditions for profit maximization are

$$\sum_{\ell=1}^{N} \gamma_\ell f_{j\ell} S_{j\ell} + (p_j - k_j) \sum_{\ell=1}^{N} \gamma_\ell f_{j\ell} (\partial S_{j\ell}/\partial p_j) = 0. \qquad \textbf{(18)}$$

By using the fact that this equation applies for all firms, we can compute the Nash equilibrium. (In a Nash equilibrium, each firm chooses its price to maximize profit assuming all competitive prices are fixed. An equilibrium occurs when no firm has a unilateral incentive to deviate from its equilibrium price; see Luce and Raiffa 1957.) We solve Equation 18 for the price-cost margins, $M = (p_j - k_j)/p_j$,

$$M = \left(\sum_{\ell=1}^{N} \gamma_\ell f_{j\ell} S_{j\ell}\right) / \left(\sum_{\ell=1}^{N} \gamma_\ell f_{j\ell} S_{j\ell} \epsilon_{j\ell}\right), \qquad \textbf{(19)}$$

where $\epsilon_{j\ell}$ is the effective price elasticity of brand $j$ within consideration set $\ell$.

By symmetry, the sales, $S_{j\ell}$, within consideration sets should be inversely proportional to the size of the consideration set, $\ell$. The fraction who consider $j$ given that they consider $\ell$ brands will be proportional to $(\ell/N)$. Finally, assume that the effective elasticity within a consideration set is a linear function of the size of the consideration set.

Letting $\beta$s denote parameters, these assumptions imply $S_{j\ell} = \beta_0/\ell$, $f_{j\ell} = \beta_3\ell/N$, and $S_{j\ell} = \beta_4 + \beta_5\ell$. Substituting these relationships in Equation 19 using $\sum \gamma_\ell = 1$ and simplifying yields the result that

$$1/M = \text{constant}_1 + \text{constant}_2 = (\sum_{\ell=1}^{N} \gamma_\ell \ell). \quad \textbf{(20)}$$

Setting $\beta_1 = \text{constant}_2/\text{constant}_1$, and inverting yields the result in the text.

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