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Abstract

We develop and test a non-HIA, two-stage choice model for low involvement categories and use a concept called "in-store brand awareness" to predict brand consideration. Theoretically, a choice model that includes consideration sets should display local price response, i.e. the phenomenon that consumers are price-rational only within a bounded set of brands. We find that price response is limited to the consumer- and occasion-specific set of brands that our model predicts as the consideration set. Local price response, as opposed to global price response, has strong implications for the structure of price competition. Cross and own elasticities become conditional on a brand's frequency of consideration set membership. Besides this theoretically and practically poignant result, the two-stage choice model fits the data and predicts choices better than the reference logit model. It also retains the attractive properties of the logit model in estimation and market segmentation. We segment consumers on the size of the consideration set and quantify the consideration formation process for these different segments. This quantification gives additional support to the concept of local price response.

Keywords: consideration sets, consumer choice, threshold models, segmentation, price response, price elasticity.
Introduction

Consumers do not devote much mental effort to a specific choice decision during shopping trips. Brand managers in mature categories thus need to make a constant effort to attract the attention of consumers. Undoubtedly responsible for this is that consumers use heuristics to reduce the mental burden of a complete comparison of all choice alternatives. This may be especially true for low involvement categories where perceptions of quality differences, or differences in product attribute space, are minor, absent, or hard to process (Carpenter, Glazer and Nakamoto, 1994), and for categories with many choice alternatives. One important heuristic for reduction of the mental burden of the consumer is offered by a two-stage choice process, in which the consumer reduces the number of choice options into a smaller subset before choosing from that subset. This subset has been termed the consideration set or choice set and has been defined as those goal satisfying alternatives that are salient or accessible on a particular occasion (Shocker, Ben-Akiva, Boccara, and Nedungadi, 1991). For slightly different but entirely consistent definitions see Hauser and Wernerfelt (1989) and Kardes, Kalyanaram, Chandrashekaran and Dornoff (1993).

We contend that, in low involvement categories, brands can be made accessible or salient through in-store arrangements, such as for example special displays. Accessibility or salience is likely to be determined at the point of purchase if the in-store environment stimulates accessibility or recall. Nedungadi (1990) points out that consideration set formation is indeed stimulus based because of the physical presence of the brands on the shelf. On the other hand, the memory literature argues that decisions of consumers are primarily based on memory recall of information and less so on external information search (e.g. Hoyer 1984, Dickson and Sawyer 1986) and that, thus, very few consideration sets are purely stimulus based (e.g. Alba, Hutchinson and Lynch, 1991). We combine these views in a process where external stimuli, such as promotion display or shelf space, may aid memory recall, or accessibility, of brands. This concept of memory recall is in essence a short-term version of brand awareness and is labeled in-store awareness.
The essence of our proposal is that only those brands with high enough in-store awareness will be inspected for choice and only those brands are by consequence in the consideration set. One implication of a two-stage choice process is that consumers do not react to prices of brands that fall outside this set. Accordingly, we propose that variability in accessibility or awareness of the brand at the point of purchase makes that prices of not all brands are processed. This absence of full knowledge of within-category prices stands to reason; shopping trips usually involve too many decisions to allow for within-category comparison of all prices. A very obvious example would be a product category such as cooled or frozen deserts, for which a super-market may stock more than 500 choice alternatives. Other, less extreme, examples may include margarine, potato-chips or non-food items such as laundry detergents.

Another essential point of our proposal is that the consideration at point-of-purchase can either be spontaneous or induced. As an example, end-of-aisle displays, assuming exposure, cause consumers to make a decision about either choosing the displayed brand or to postpone the choice decision and visit the regular (shelf) category location. This decision is compulsory, and makes the promoted brand considered for choice in the literal sense of the word. In this example, consideration is not necessarily spontaneous or even voluntary, but may be induced by increasing point-of-purchase awareness to a point where the consumer has to make a choice decision in front of the display.

Traditionally, the formation of consideration sets has been linked to the position of alternatives in product-attribute space (e.g. Swait and Ben-Akiva 1987, Lattin and Roberts 1991, or for a historical overview, Fotheringham, 1988). While this approach is valuable in cases such as choice of transportation mode or spatial choice (Borgers and Timmermans 1987, Meyer and Eagle 1982), its underpinnings may not apply to buying behavior in low-involvement product categories. First, this liaison implies that the consideration set of a given household is static across purchase occasions. While from the memory literature
consideration set membership appears to be dynamic and reactive to recall-enhancing arrangements in the store. Second, the above approach assumes that consumers evaluate all alternatives in attribute space which assumes, still, a very laborous choice process of the consumer.

Some attention has risen for the dynamics of consideration sets (Kanetkar and Nedungadi, 1994), and its determining factors (Shocker, Ben-Akiva, Boccara, and Nedungadi, 1991). Notwithstanding this attention, the consideration set formation process has, empirically, remained largely unquantified; the phenomenon of local, as opposed to global, price response has not yet been discussed; and its implications for the structure of price competition have not yet been studied. We address these voids in the literature by specifying, operationalizing, and testing a two-stage choice model that allows us to investigate these phenomena.

In doing so, we propose that the consideration set formation can be tracked by making reasonable assumptions about its determinants. If these determinants can be tracked over time, inferences about the underlying consideration set composition and size are secured. We validate the consideration sets with an independent test on deterministic approximations of the true consideration set. The results of this test are extremely supportive of our assumptions.

We contribute to the literature in the following directions. First, we model a choice process in which the consumer is only processing information of a selection of brands. This model is innovative with respect to (i) the representation of a dynamic consideration set formation process, (ii) the use of a nonlinear (threshold) awareness criterion for inclusion in the consideration set, and (iii) the recognition of a fundamental difference in impact of marketing mix variables that generate in-store brand awareness vs. others that generate brand value. Second, we show that the implicit logit assumption of global price response is unsupported, and that it overstates (i) the vulnerability of brands that are frequently in the set and (ii) the competitive clout of brands that are infrequently in the consideration set. Third, we show that the inferred size of the consideration set is cross-sectionally distributed across
members of a population and we show how within homogenous segments the consideration set varies over purchase occasions. Finally, we add to the managerial understanding of price discount/end-of-aisle promotions and complement Inman, McAlister and Hoyer's (1990) argument that promotional displays can be taken by consumers as a proxy for a price cut.

This paper is structured as follows: In the next section, we present a modeler's account of the two-stage choice process and derive a testable choice model. We operationalize our model in section 3 and report, in section 4, the estimation results with our model using scanner data from the laundry detergent category. The model's substantive results are in section 5. We conclude and suggest guidelines for future research in section 6.

**Model**

At every shopping occasion, consumers are hypothesized to form a consideration set of brands that they will evaluate for choice. For these consumers, consideration set membership is deterministic. For low involvement categories, the consideration set formation happens in the store, and is based on the capacity of each choice alternative to attract the attention of the consumer and to a reach short-term awareness cut-off level or threshold. We view the in-store environment as being "noisy" and full of conflicting stimuli; the threshold is the minimal level of awareness to break through the background noise. Consideration for low-involvement purchase decisions is thus a largely passive, and not very effort-intense, process on behalf of the consumer. In the second stage, consumers choose the utility maximizing alternative from the restricted choice set. The mathematical formalization presented below is the analyst's representation of the consumer's process.

**Consideration set formation.** We assume that every consumer \( h \) has a specific, latent, threshold of in-store awareness \( \Theta^h_i \) to consider a brand \( i = [1 \ldots n] \). Denote in-store awareness of brand \( i \) for household \( h \) at occasion \( t \) by \( S^h_{it} \). From a modeler's perspective neither in-store awareness \( S^h_{it} \) nor the cut-off value \( \Theta^h_i \) can be observed or known with certainty.
This means that, for the analyst, consideration set membership of a brand is probabilistic. The distribution of inclusion probabilities across brands has two characteristics that we address separately: (i) concentration and (ii) magnitude. The first characteristic alludes to the polarization of inclusion probabilities, whereas the second characteristic defines the absolute magnitude of the probabilities. A Thurstone model for $S_{it}^h$ and $\Theta_t^h$ can be used to deal with the modeler's uncertainty about the concentration of inclusion probabilities, which is rooted in the uncertainty about the brand awareness and the awareness threshold:

$$S_{it}^h = \theta_{it}^h + \xi_{it}^h, \quad i := [1, \ldots, n]$$

and

$$\Theta_t^h = \theta_t^h + \xi_{n-1,t}^h,$$

Brand $i$ is considered by a consumer $h$ at purchase occasion $t$ if $S_{it}^h > \Theta_t^h$. We assume that the $[n + 1]$ random components are i.i.d. draws from the Gumble or Extreme Value Type I distribution. Note that the $(n + 1)^{st}$ random component is common across brands and assures that $\Theta_t^h$ is a common threshold across brands for a given purchase occasion. Under the distributional assumptions, the relative magnitudes of the probabilities that a consumer $h$ includes brand $i$, $(i = 1, \ldots, n)$ in consideration set $M$ at occasion $t$ are given by:

$$\Pr(i \in M)^h_t = \frac{\exp(s_{it}^h)}{\exp(s_{it}^h) + \exp(\theta_t^h)}, \quad i := [1, \ldots, n]$$

(1)

The magnitude of the distribution can be altered without altering the concentration of it by multiplying all inclusion probabilities $\Pr(i \in M)^h_t$ with a constant. As will be shown, this multiplication factor has no bearing on the choice probabilities.

*Choice from the consideration set.* Consumers compare utilities $V_{it}^h$ for alternatives $i$ that are in the consideration set and choose that alternative that maximizes utility. The modeler, however, does not know the exact composition of the consideration set. One rational option
for the modeler is to use a Bayesian approach in which the information about consideration and brand choice is sequentially combined at each choice occasion. This updating process is the probabilistic equivalent of expressing that consideration is a necessary condition for choice.

In a Bayesian context, the distribution, equation (1), of the likelihood of brand consideration is treated as a non-diffused, non-normalized prior distribution for choice.

By normalizing, define this prior distribution of choice as:

\[
\pi_{it}^h = \frac{\Pr(i \in M)^h_t}{\sum_{j=1}^n \Pr(j \in M)^h_t}, \quad i = [1, \ldots, n]
\] (2)

To update the prior distribution with information about the brand evaluations, Bayes’ rule applies:

\[
P_{it}^h = \frac{\pi_{it}^h \cdot Q(i|i \in M)^h_t}{\sum_{j=1}^n \pi_{it}^h \cdot Q(j|j \in M)^h_t},
\] (3)

where \(Q(i|i \in M)^h_t\) is the average conditional probability that consumer \(h\) chooses brand \(i\) out of a specific consideration set \(M_i\) at occasion \(t\), given that \(M_i\) includes brand \(i\), and \(P_{it}^h\) is the unconditional choice probability. Many consideration sets may include alternative \(i\).

Writing the universal set of consideration sets as \(M\) and the set of those that include \(i\) as \(M_i\), where \(M_i \subseteq M\), we can write the average probability of choice over all consideration sets that include \(i\) as:

\[
Q(i|i \in M)^h_t = \frac{\sum_{\forall M_i \subseteq M_t} P_M(i|M_i)^h_t \cdot P_M(M_i)^h_t}{\sum_{\forall M_i \subseteq M_t} P_M(M_i)^h_t},
\] (4)

where \(P_M(M_i)^h_t\) is the probability that \(M_i\) is the consumer’s consideration set, and \(P_M(i|M_i)^h_t\) is the probability that brand \(i\) is the utility maximizing alternative of \(M_i\).

We now make an assumption that presumes a regularity of \(Q^h_t(i|i \in M)\) across all brands \(i\). Specifically, we assume that the average conditional choice probability for \(i\) over all
consideration sets that are an element of $M_i$, is proportional to the choice probabilities of a regular logit model over the global choice set, i.e. that

$$
Q^h_i(i|i \in M) \propto \frac{\exp(V^h_{it})}{\sum_{j=1}^{n} \exp(V^h_{jt})}, \quad \forall i = [1, \ldots, n] 
$$

We claim that this assumption about the (weighted) mean of the conditional choice probabilities is very mild. To appreciate the mildness of the assumption we stress that consistency with the Independence of Irrelevant Alternatives (IIA) axiom is not implied; $Q(i|i \in M)$ is the mean of the conditional choice probabilities over consideration sets $M_i \in M$. Hence, the assumption only claims weak regularities among the individual conditional choice probabilities that lead to that mean. Hence, for two given subsets, $M_1$ and $M_2$, both including alternatives $i$ and $k$, the assumption does not imply any regularity about $P(i|M_1)$ or $P(i|M_2)$ separately, i.e. it does not preclude context dependent choice behavior (e.g. Simonson and Tversky 1992). In other words, it does not imply that the ratios $P(i|M_1)/P(k|M_1)$ and $P(i|M_2)/P(k|M_2)$ are constant. Rather it implies that $P(M_1) \cdot P(i|M_1) + P(M_2) \cdot P(i|M_2)$ obey a certain regularity, which is a much weaker assumption than the logit model. Even context-driven preference reversals are admitted by this assumption, because of the same reason that a mean does not imply anything of the dispersion of the individual choice probabilities.

Under the above assumptions, the modeler's representation of the consumer's choice process can be summarized by the following probabilities of choice:

$$
P^h_{it} = \frac{\pi^h_{it} \cdot \exp(V^h_{it})}{\sum_{j \in C} \pi^h_{jt} \cdot \exp(V^h_{jt})} 
$$

Note that, consistent with our previous discussion, it is only the relative magnitude of the inclusion probabilities that is relevant in equation (6) and not the absolute magnitude. Multiplication of the $\pi^h_{it}$'s by a constant that is common across brands does not affect the choice probabilities. The absolute magnitude can be obtained as follows, however. As the
consideration set can not be empty, at least one of the inclusion probabilities needs to be 1.0. Operationally, therefore, this scaling factor is determined by the maximum inclusion probability for any given choice occasion. Rescaled inclusion probabilities, i.e. inclusion probabilities $\pi_t^h$, divided by their maximum given $t$ and $h$, are written as $\bar{\pi}_t^h$ and are needed when the consideration set size is inferred.

The particular form of choice models that is implied by equation (6) has been used before by Fotheringham (1988) for store choice decisions and by Vanhonacker (1994) to model typicality of brands in the choice process. While the mathematical formulation of our model bears resemblance to these studies, our operationalization of the model sets it clearly apart.

**Operationalization**

Underlying the operationalization, is an attempt to categorize explanatory variables into two, mutually exclusive, categories: (i) in-store awareness generating variables and (ii) brand value or brand utility generating variables. The first category affects the inclusion probabilities, i.e. the composition of the consideration set, while the second affects the choice out of this set.

**In-store awareness** generating descriptors of the brand, do not generate brand value per se. There is no compelling reason why a consumer would truly derive brand value from in-store announcements such as promotion displays (assuming no price cut) or large shelf space allocation. It is however quite probable that these visual enhancements will direct the consumers attention to the availability of the brand as a choice option, i.e. raise awareness in the store for the brand's choice candidacy. We hypothesize that in-store awareness, i.e. how aware a consumer is of a brand at the point-of-purchase, is increasing in (i) recent usage (Alba, Hutchinson, and Lynch 1991, Deighton, Henderson and Neslin 1994, Kanetkar and Nedungadi 1994), and (ii) in external cues in the choice environment (Hauser and Wenerfelt 1989, Nedungadi 1990) that raise visibility of the brand. This process of formation of in-store awareness is consistent with Alba, Hutchinson and Lynch's (1991) view that the consideration set is build from recognition and recall processes, in which recall is memory
based and recognition is more based on in-store cues, and with Nedungadi (1990), who finds that consideration set generation is closely linked to accessibility and extend retrieval cues. Value generating descriptors of the choice option, on the other hand, do not necessarily raise the attention of consumers towards the brand, especially not in low involvement decisions where cross-brand comparison of brand information is low. As an example, there is no compelling reason why high or low ticket price would lead to less or more in-store awareness of the brand. Brand value is hypothesized to be generated in the price-quality domain (Allenby and Rossi 1991) or price-preference domain (Lattin and Bucklin 1989). We adhere to Latin and Bucklin (1989), and describe the product value in terms of monetary variables and preference.

Below is an attempt to operationalize these concepts with widely available scanner data.

**In-store Awareness.** In-store brand-awareness is operationalized as an increasing function of (i) recency of choice, (ii) the in-store location of the brand, and (iii) the allocated shelf space.

We define recency of choice as: $Y_{i,t}^h = (1 - \delta_i^h) \cdot \lambda^{rec} \cdot Y_{i,t-1}^h + \delta_i^h$, where $\delta_i^h$ is 1 if brand $i$ was chosen by consumer $h$ at the previous choice occasion and where $\lambda^{rec}$ is a smoothing constant. This variable thus assumes the value 1.0 for the last chosen brand, and is exponentially sloping downwards for other brands. Note, that although “optically” similar, this measure is quite different from the Guadagni and Little (1983) loyalty measure in spirit and in mathematical formulation. We discuss the differences shortly hereafter.

**Promotion display:** We define $Y_{21}^h(t) = 1$ if the brand is on end-of-aisle display, and $Y_{21}^h(t) = 0$ in the other case. This variable, among others, captures the visibility of the brand at the point of purchase and stimulates recall and recognition of the brand as a choice option.

**Allocated shelf space:** $Y_{31}^h(t)$ measures the size of the shelf space (facing) allocated to each brand in meters. As with the previous variable, allocated shelf space will increase the consumer’s in-store awareness of the brand.

The deterministic part of the in-store awareness construct, $s_{it}^h$, in equation (1) is opera-
tionalized as a linear combination of the above measures.

**Perceived value of alternatives.** The brand value construct is conceptualized as a combination of brand preference and monetary substitution value. We propose three different measures:

**Inherent preference:** We operationalize this measure in two parts. The first part, is an overall preference measure, \( a_{0t} \), that consists of a set of dummy variables, while the second part, \( X_{1t}^h \), is a consumer specific preference measure that is computed as the relative choice frequency over an initialization period of the data (Lattin and Bucklin 1989).

**Unpromoted price:** \( X_{2t}^h(t) \), captures the regular price of the alternative. In cases where end-of-aisle promotions were accompanied with a price cut, this measure is equal to the actual in-store price plus the price cut.

**Price cut:** \( X_{3t}^h(t) \) measures the price cut in monetary terms. Price cut are (arbitrarily) expressed as positive numbers, hence the larger \( X_{3t}^h(t) \) the deeper the price cut is, and the less the price actually paid is.

The brand value construct, \( V_{1t}^h \), in equation (6) is operationalized as a linear combination of the proposed measures.

**Discussion.** We did not use the Guadagni and Little (1983) loyalty measure as an explanatory variable because, in the present context, its meaning is ambiguous. We claim that the loyalty variable can be split into the preference measure \( X_{1t}^h \) and the recency measure \( Y_{1t}^h(t) \). Our justification is as follows: It is an empirical fact that the brand by brand geometric mean of the G&L loyalty measure for a consumer over its entire purchase string is either extremely close or equal to the relative purchase frequencies of the brands that were purchased by that consumer (the G&L measure adds to 1 across brands, and is bounded between 0 and 1). This is to say that, cross-sectionally (across consumers), the G&L measure performs the same role as our \( X_{1t}^h \) preference measure in the value function. Additionally, the G&L measure is increasing in the recency of choice. Hence, longitudinally, the G&L
measure is analogous to our recency of choice measure in the awareness function, yet the recency measure is reset to 1 after a choice of the corresponding brand, whereas the G&L measure moves geometrically up and down—depending on recency of choice—around a level that is identical to the stationary multinomial probabilities of choice for a given consumer. Thus, the combination of “recency of choice” and “inherent preference” are both present in the G&L loyalty measure, yet the different influence that both have on choice can not be parceled out. In this respect the measurement proposed above is more flexible and enhances a more detailed understanding of the function of the loyalty measure, which has been criticized before for its ambiguous meaning (e.g. Chintagunta, Jain, and Vilcassim, 1991).

**Empirical Analysis**

We estimate three model specifications. The Guadagni and Little (1983) logit model was used for comparison and accounts for the first model. The consideration set model (CSM) as explained and operationalized above is the second model. Finally, we re-estimated the point-of-purchase consideration model while accounting for heterogeneity in consideration set size (HCSM). Through their operationalization, all models account for consumer heterogeneity in brand preferences.

Data. We used regular powder detergent data from the Nielsen Scan 7000 system in France. The physical quality differences between these brands are minimal (50 Million de Consommateurs, 1990), and the number of brands is large (13). The size of the global choice set in the detergent category makes it unlikely that consumers investigate and compare price and quality of all brands before choosing at each purchase occasion. We randomly selected 169 households out of 1147 who have made at least 12 purchases. The total sample size was \( N = 2979 \) observations. On average families in our data set made 17.62 purchases over a two year period. The choice sequence of each household was chronologically divided into three parts: approximately one-third was used for initialization purposes (\( N_1 = 987 \)), the second part was used as an estimation sample (\( N_2 = 1005 \)) and the remainder (\( N_3 = 987 \)) was used
as a hold-out sample for validation purposes. Table 1 describes the laundry detergent data set for 12 brands—plus a brand labeled “other”—in terms of average price paid, average promotion intensity, average shelf space, and overall purchase share in the estimation sample. No advertising exposure data were available for this category. Fortunately, however, advertising is expected to play only a moderate role in formation of point-of-purchase awareness because (i) it is well established that dynamics of advertising do not lead to dynamics in choice to the same degree as for instance promotion does, and (ii) in mature categories advertising response is typically very low and confounded with the preference measures.

[Insert Table 1 here]

*Estimation Procedure.* Estimation was done, through a maximum likelihood procedure, using a Fortran based steepest gradient search with the Fletcher Powell algorithm. When only consumer heterogeneity is assumed in inherent brand preferences (the Logit and CSM models), the likelihood function is as in Guadagni and Little (1983). In cases where consumer heterogeneity with respect to the size of the consideration sets was estimated, the likelihood function, including support points \( s = 1, \ldots, S \) and associated probability mass \( \phi_s \) is detailed in Chintagunta, Jain and Vilcassin (1991, p. 422).

The Guadagni and Little (1983) Logit model was estimated, along with the smoothing coefficient of the loyalty variable. Details are in Fader, Lattin and Little (1992). The estimated value of the smoothing parameter was found at 0.65, which is very low. The procedure of Fader, Lattin and Little (1992) is however retrieving the correct value; more conventional values of the parameters where tried with the invariant result that overall fit of the model decreases significantly. The model with a smoothing parameter of 0.65 represents the “best fitting” variant of the logit model.

All parameters of the CSM model are statistically identified up to a metric, i.e. the model can be estimated in one stage by fixing one of the brand constants to a zero. The method by
Fader, Lattin and Little (1992) to estimate the smoothing parameter of the recency variable, can unfortunately not be used here because the derivative of the recency measure with respect to $\lambda^{rec}$ is non-zero only for selected events (when the brand is not chosen recently). We used a grid search and found that the smoothing parameter that best represents the data is equal to 0.79.

Finally, to estimate the HCSM model, we allowed the difference between point-of-purchase awareness and the threshold of inclusion, $S^h_{it} - \Theta^h$, to be different across households. We estimated latent segments by using a semi-parametric approach. Details are in Chintagunta, Jain and Vilcassim (1991). Since it is the difference, $S^h_{it} - \Theta^h$, that determines consideration set membership, it is possible to either make $S^h_{it}$ or $\Theta^h$ household specific. We chose the first option because by anchoring on the threshold, the model allows for a simple comparison of responses to promotion display and shelf-space across households. In addition, since we were interested in finding out whether households are more apt to inspect and compare prices of brands in the consideration set, we also included price and price-cut variables in subsequent analysis\(^3\). We approximated the underlying heterogeneity of consumers by two separate segments. Based on the Akaike information criterion, this amount of segments is optimal.

[Insert Table 2 here]

**Results.** The estimation results are summarized in Table 2. The overall fit of the Logit model is good with an adjusted $\hat{R}^2$=0.558. The parameter estimates all have the correct sign, but lack significance for the marketing mix variables. The only in-store variable that is strongly significant is promotional display.

The CSM model fits better than the logit model and results in an improvement in adjusted $\hat{R}^2$ of 1.7% over the logit model’s fit; the $\hat{R}^2$ is 0.575. All the parameter estimates have the right sign but -as is the case with the logit model- lack significance on the marketing mix
variables price, price cut and shelf-space. The threshold for inclusion in the consideration set, the recency measure and the preference measure are all significant at the 0.01 level or lower.

In the HCSM model, two distinct segments underly the entire sample. One segment has a broad consideration set and one segment has a concentrated (small) consideration set. The first segment consists of 31% of all households, while the second consists of 69% of the households. The two segments are labeled “in-store sensitive” and “loyal”, respectively. The “in-store sensitive” segment shows a very strong sensitivity to promotional signal and shelf space coupled with a relatively small estimate of the recency variable. This lower dependence on the past suggests that the consideration set for households in this segment is dynamic and follows the in-store environment. The concentration of the cross-brand distribution of inclusion probabilities can be measured by the Herfindahl index. This index is equal to \[ \sum_{h=1}^{169} \sum_{t=1}^{T^h} \sum_{i=1}^{13} \left( \pi_{it}^h \right)^2 / 1005 \]; we recall that the inclusion probabilities \( \pi_{it}^h \) are normalized to add to 1 across brands (see equation (2) for the segment unspecific equivalent). Low values indicate low concentration, high values indicate high concentration. The minimum value for the index is 0.08 (1 over 13) and the maximum value is 1. This measure of concentration is 0.24 for the in-store sensitive segment. Inclusion probabilities are thus very dispersed.

In the loyal segment, the single most important measure that drives the consideration set formation is recency of choice. Households in this segment display no sensitivity to store variables, not even to promotional display. This exclusive reliance on recency of choice suggests that the distribution of inclusion probabilities is highly concentrated which is confirmed by a Herfindahl index of 0.55.

An alternative interpretation of our segmentation, given that we allow price response to be heterogenous, is high-price brand and low-price brand buyers. If this were the case, price would have to be included in the consideration set generation process and our model would
have to be adjusted for this. This interpretation is, however, most uncompelling. Prices of brands range from 13.35 to 17.10. The standard deviation of the cross brand prices in the estimation sample is 1.92, whereas the average price paid in segment 1 is FF 15.34 and in segment 2 FF 15.62. The difference between the prices paid in the two segments is only 0.28, which is close to one-seventh of the standard deviation in the cross-brand price data. If one segment would be a low-price brand segment and the other a high-price brand segment, the average prices paid in the two segments would need to portray a significant difference. It clearly does not.

**Predictive Validation of the Models.** We validated the estimated models on a hold out sample. Besides the log likelihood criterion in the hold-out sample, the following validation measures were used. The hit-rate is defined as usual. The average choice probability (ACP) is defined as the average predicted probability for the actual choice. The variance of the choice probability (VCP) is defined as the variance in the ACP measure. High variance in the predicted probabilities of chosen brands indicates that certain choices are predicted very well and others are not. All other things constant, a low variance is preferred to a high variance. The logit model is an increasing marginal utility model in choice and will thus have more difficulty predicting switches than the CSM model which is a constant marginal utility model. We expect superiority of the CSM and HCSM models on this measure. To validate the HCSM model, we assign households to segments using Grover and Srinivasan’s (1989) Bayesian procedure.

The results are summarized in Table 3. For reference, we report the value of the measures in both the estimation sample as well as the hold-out sample.

[Insert Table 3 here]

The validation results are very good for all three models, with the best overall predictive validity for the HCSM model. In the estimation sample the logit model is marginally in-
ferior to the other models on all three measures. In the hold-out sample, the logit model is marginally better on hit-rate and the average predicted choice probability, but has, as anticipated, a much higher variance of the predicted choice probabilities; 33% compared to the homogenous consideration set model. We attribute the slightly better hit-rate and ACP of the logit model to the fact that in the estimation sample there is 4% less switches than in the hold-out sample. This also explains why the hold-out results are generally better than the diagnostic results in the estimation sample. Finally, the validation results of the HCSM model are based on a rational, yet imperfect, method to assign households to a certain segment. The validation results for this model are subject to the imperfectness of this method and could potentially even be improved.

Process Validation. It is possible, even in abscense of factual data of consideration set membership, to validate the outcome of the consideration set formation process. Consumers choose only among brands in the consideration set and therefore prices of brands outside the consideration set should not affect choice, even if there is, objectively, a better deal outside the set. If the followed approach has been successful at retrieving the consideration set or the relevant choice set, the price response within the consideration set should be negative and significant, whereas the price response associated with brands outside the predicted set should be zero. Testing these implications renders an independent validation of the consideration set formation process, because the inclusion probabilities are based on in-store awareness and not on price. The testing procedure followed is:

Using predicted inclusion probabilities from the HCSM model and a cut-off criterion on these probabilities, we determine consideration set membership. Subsequently, we estimate two separate price effects, $\beta_1$ and $\beta_3$, conditional on membership of the predicted consideration set or the complementary set, respectively. To be beyond reproach, we do not estimate price effects with the CSM model, but with a Logit model that includes brand intercepts, recency, the preference measure and price. We use price data that are rescaled to have a zero mean.
In Table 4, we report the estimated price effects in and outside the predicted consideration set and the log likelihood for the estimated models. We report the results for 4 alternative cut-off criteria, from 0.5 down to 0.2. We do this for two reasons. First, although the criterion, \( \pi^h_{it} > 0.5 \), produces the "maximum likelihood" consideration set, the size of this set is always an underestimate of the expected size. Imagine 2 brands that both have an inclusion probability of 0.4; both will not be in the maximum likelihood consideration set, whereas the probability that at least one of them is in the set is much larger than 0.5. Second, if the set is over-estimated (low cut-off value), the price response over the complementary set should still be zero.

[Insert Table 4 here]

Table 4 accords extremely well with our predictions. There is simply no price response to prices of brands which are predicted to be outside the consideration set. We wish to draw attention to the fact that the number of brands outside the consideration set is more than six times higher than in the consideration set (see next section). Hence the odds of finding statistically significant results are stacked against our test, both with respect to the price effect in- as well as the price effect outside the set. This adds strength to our finding.

Finally, note that the more certain the membership of the complementary set (i.e. the lower the cut-off value), the lower the price response, as was hypothesized.

We conclude that, empirically, our approach has identified the sets over which consumers are price sensitive. These sets vary by consumer and purchase occasion. We have made a theoretical argument that in-store awareness determines membership of these sets for low-involvement categories and the above test seems to support our argument. This theoretical argument in turn is based on the definition of consideration sets given by Shocker, Ben-Akiva, Boccaro and Nedungani (1991). The test on the differential price sensitivity, cautiously, suggests that the approach is useful in determining the consideration set of consumers for low involvement categories, although more research is warranted.
Substantive Results

In this section, we interpret the estimation findings in three ways. First, we address the quantification of the consideration set formation process, and demonstrate how to infer the size of the consideration set for consumers in both segments. Then, turning to the managerial implications of consideration sets, we take a brand perspective and contrast clout and vulnerability measures that are obtained from (i) the local price response above, and (ii) the global price response that is implicit to the logit model. Finally, we discuss the role of promotions in our model and add to a result that was found by Inman, McAlister and Hoyer (1990).

Inferring the consideration set size. For each household and each purchase occasion the distribution for the size of the consideration set was evaluated. We calculated the inclusion probabilities seperately for households in segment 1 and segment 2 using the HCSM model. Subsequently, the individual probabilities were ranked highest to lowest, regardless of brand name. Note that, as discussed in the modeling section, the highest ranked inclusion probability is by definition 1.0. To calculate the probability that a consideration set of size \( L = \{1, \ldots, 13\} \) occurs, we evaluate the likelihood of all possible permutations of size \( L \) and sum their likelihoods per size. The likelihood of for instance a consideration set of size three and permutation \( C = \{1, 2, 3\} \) (this is one of 66 permutations for a consideration set of size 3, acknowledging that the highest ranked is always in the consideration set) is calculated as:

\[
P_t^h(1, 2, 3) = \prod_{l=0}^{3} \frac{1}{13-2} \prod_{j=4}^{13} \left( 1 - \tilde{\pi}_j^h \right), \quad \tilde{\pi}_1^h = 1.0
\]

The implicit independence assumption in this equation, which is also used by Hauser and Wernerfelt (1989), is in this application particularly mild because, given limited quality
differentiation, the global choice set is not likely to be consistently divided into two or more groups along this dimension. Also, the inclusion probabilities across brands are partly determined by a store environment that can be seen as a set of random shocks. Across brands there will therefore not likely be any systematic correlation between inclusion probabilities. Finally, we averaged the distributions within segments. The distribution of the consideration set size for the two segments is shown in Figure 1. The shapes of the two distributions are intuitive and strikingly different.

[Insert Figure 1 here]

The interpretation of the two distributions in Figure 1 is that, for instance, the inferred size of the consideration set in the loyal segment is 1 for 69% of the purchase occasions, 2 in 25% of the purchase occasions, 3 in 5% of the purchase occasions and 4 in 1% of the purchase occasions. The average consideration set size over all purchase occasions is 1.38. By consequence, the choice stage in the consideration set/choice process becomes a choice by default in most cases and price comparisons within the consideration set are not possible. It is thus not surprising that price and price-cut have no effect on consumers in this segment.

In the consideration set for the in-store sensitive segment, there are always "the other brand(s)". The size of the consideration set is 1 in only 25% of the purchase occasions, whereas the expected consideration set size is 2.42.

We observe that these inferred consideration set sizes correspond in magnitude very well with Lehmann and Pan’s (1994) reported values of true consideration set sizes, which adds some external validity to the process that we model.

We also note that the expected size of the consideration sets coincides with the sizes that would be obtained by approximating the set with the cut-off criterion \( \hat{\pi}^h > 0.3 \) (recall that the \( \hat{\pi}'s \) are the transformed inclusion probabilities, such that the consideration set is never empty). The average size of approximated consideration sets with this criterion is 1.37 for
the loyal segment and 2.51 for the in-store sensitive segment.

Compared to the size of the global choice set of 13, the inferred consideration sets in both segments are of modest size. This indicates that the mental burden for consumers to make a choice decision is much less than one-stage choice models or full comparison two-stage choice models suggest. The full specification of the choice model, equation (6), is merely accounting for the modeler’s uncertainty and it is therefore the analyst’s burden to compare all alternatives, not the consumer’s.

\textit{Brand level analysis.} Brand managers are interested in finding out how their brand share responds to price changes of their own brand and other brands. Kamakura and Russell (1989) use individual level analysis to derive measures of competitive clout and vulnerability, and provide managers with information about the effects of price changes. These measures are based on the price elasticities that are implied by the logit model, assuming global price response. However, the notion of consideration sets and the empirical support in Table 4, disqualifies global price response as a tenable assumption for the calculation of elasticities. It thus stands to reason to derive the elasticities using local price response. Consequently, price elasticity becomes dependent on the frequency of membership of the reduced set. We illustrate the different implications of local and global price response with an example.

Assume a global choice set with three brands $H$, $L_1$, and $L_2$ and two types of consideration sets, $(H, L_1)$ and $(H, L_2)$, both with equal occurrence. A price decrease of $H$ will affect both $L_1$ and $L_2$’s share. However, a price decrease in either $L_1$, or $L_2$, will only affect half of the choice decisions involving brand $H$. Hence, brand $H$’s vulnerability is less than implied by global price response. By the same token, $L_1$’s competitive clout is lower than implied by the global price response because lowering its price will only affect half the population. Hence, we hypothesize that high consideration-set-membership brands (brand $H$) will be less vulnerable than implied by the logit model and that low consideration-set-membership brands (brands $L_1$ and $L_2$), will have less clout than implied by the logit model.

Own and cross price-share elasticities were calculated in both cases by increasing, one by
one, a brand's price by 1%. The Logit model and the HCSM model respectively were used to compute the changes in choice share of all brands and elasticities were calculated directly from these changes (e.g. Kamakura and Russell 1989, Bucklin, Gupta, and Siddarth 1994). We approximated the consideration set using the HCSM model and the criterion \( \tilde{\pi}_{it}^h > 0.3 \). This seems a good approximation because (i) we observe from Table 4 that there is no price response outside this set and (ii) as mentioned before, the size of the set obtained by this criterion is virtually identical to the expected size of the set. We concentrated on the in-store sensitive segment\(^4\). The measures for competitive clout and vulnerability are defined in Kamakura and Russell (1989, p. 386).

[Insert Figure 2 here]

Figure 2 visualizes the 12 brands (the category "other" is not really a brand) in the clout-vulnerability plane. For interpretation purpose, we list the frequency with which the brands occur in the predicted consideration set, in the top graph. In the lower graph, this frequency is 1.0 for all brands. The ordering of the brands in the two graphs is typically the same on both axes. However, the shape of the shaded areas that cover the location of brands, are very different. As opposed to the clout-vulnerability data of the logit model, in which the locus of brands form a steadily declining zone, the shaded area of the top graph offers a much more polarized view of the clout-vulnerability data. In the top graph, brands with high membership frequency are the winners and the brands with low membership frequency are the loosers. Among the six "top" brands in the predicted consideration set, five are in the horizontal zone (higher competitive clout, lower vulnerability) of Figure 2(i). The vulnerability of each top-six brand is indeed lower in Figure 2(i) compared to Figure 2(ii), as hypothesized. Among the bottom six brands five are in the vertical zone of Figure 2(i), and all six have lower competitive clout than predicted by the logit model, again as hypothesized. The high competitive clout position of Omo in the top graph compared to the bottom graph, maybe suggests that Omo and Ariel are less frequent in one consideration
set than implied by the independence axiom.

The locus of brands around the origin in Figure 2(i) is much more "crowded" than in Figure 2(ii). For example the area bounded by Clout<0.4, and Vulnerability<0.4, contains 7 brands based on local price response and only 1 brand based on the, incorrect, assumption of global price response. The marketing budget of the 7 brands in this region should thus not be depleted by price discounts, whereas some of these brands have substantial competitive clout under global price response. The brands that are caught at the origin (low clout, low vulnerability) promote up to 10% of the purchase occasions. The large majority of these promotions include price discounts, which seem waisted, because not much share is gained by these discounts. Much more is to be gained from increasing in-store visibility and in-store awareness (for instance promote without the price-cut). On the other hand, brands like Ariel and Omo probably should use price discounts in the in-store sensitive segment.

Summarizing, from a brand's perspective, high in-store awareness and thus high consideration set membership, creates low vulnerability and high competitive clout. This is because brands compete head-to-head in a very limited sense. To the extend that brands use promotion displays to create this in-store awareness, promotion works to increase own competitive clout, so that future price cuts are more effective. This explanation is supportive to Lal’s (1990) notion that promotions may impede competition. It is intriguing to speculate that Ariel is aware of this, not only because they use end-of-aisle promotion displays more than three times as much as the industry average, but also because many times there is no price cut associated with this display.

*The dual effect of end-of-aisle/price discount promotions.* In the introduction, we argued that the effect of end-of-aisle promotion displays is different from the effect that an accompanying price cut will have. One is, in our terms, an awareness creating variable, while the other has a conditional choice effect. Inman, McAlister and Hoyer (1990) and Inman and McAlister (1993) have argued that consumers may take promotion signals as a proxy for a price-cut. Hence, the explanation by Inman, McAlister and Hoyer (1990) stresses the
possibility that consumers take promotional signals as a sign of lower-than-usual price. This is complementary to our finding which focusses around the effect that promotions induce comparisons of prices by enlarging the consideration set. Typically, in the in-store sensitive segment, this involves a comparison of the price of the brand that is on promotion and the price of the brand that was purchased last. The two explanations, albeit different, are not rival but complementary ones. Consumers who infer that prices are lower-than-usual when a brand is promoted, make an implicit intertemporal intra-brand price comparison. Our explanation adds with the complement of that effect, namely that promotional signals stimulate a intratemporal interbrand price comparison through an inclusion into the consideration set.

Conclusions and future research

We developed and tested an individual level choice model that focusses on the role consumers' awareness for brands at the point-of-purchase, and the subsequent formation of a consumer- and occasion-specific dimished choice sets. We have termed these sets the consideration set, using the definition of Shocker et al. (1991). These sets have the empirical property that consumers' price response is limited to the brands within a given set (local price response). We purport that the link between consideration sets and local price response is not only theoretically appealing, but has strong and practical implications as well. The price elasticities that are inherent to local versus global price response are strongly different as is, by consequence, the structure of price competition. In turn, the structure of price competition has become conditional on the frequency with which the a given brand enters the consideration set. It can be argued that, instead of spending marketing resources on price discounts, most brands in our empirical application should first try to increase in-store awareness and try to enter the consumers brand choice process.

This process of choice has been tailored to low-involvement categories in the present paper. We postulated that the consideration set formation process of a consumer is passive in such categories. More specifically, whereas choice was seen in this paper as the active
processing of brand information (price in our case), consideration is based on a brand’s capacity to attract the attention of the consumer, i.e. to invite the consumer to process brand information given limited allocation of mental resources on the part of the consumer. Our model explicitly accounts for the situation where unconsidered brands are not processed at all. The empirical finding of local price response strongly supports this view.

Substantively, what may be learned from this paper is that brands need to compete for limited mind space (adapted from Corstens and Corstjens, 1994, “Stor wars: the battle for mind space and shelf space”). Overall, in 95% of all purchase occasions, the size of consideration sets is less than or equal to 3 alternatives, whereas the global choice set involves many more alternatives. Our suggestions for future research will be directed towards firm’s actions to win battles for limited mind space.

Future Research. There exists a link between choices by default (unit size consideration set) and purchase behavior. Given memory dependence of the in-store awareness (e.g. Alba, Hutchinson and Lynch, 1991), we may assume that unit size of the consideration generally implies a repurchase. We find that in the loyal segment as well as in the in-store sensitive segment, the tendency to switch, given a consideration set of size 2 or more, is very close. This raises research questions about the underpinnings of loyalty. Is loyalty indeed related to a unit-size consideration set? If so, which brand enters the set. We see a seminal role here for advertising, which can be translated in the following key question. Does advertising have more of an effect on the structure of share (between “loyals” and “switchers”) than on the absolute amount of share? This questions may shed new light on advertising response research, because it potentially explains why advertising rarely has a strong choice effect (see for example Deighton, Henderson and Neslin 1994).

This topic is currently pursued, as well as external validation of the consideration set formation process.
Endnotes

1. It is perhaps instructive to point out that we expect the threshold to be category dependent.

2. This magazine, which is the French equivalent of Consumer Reports, rated various brands in measurable quality criteria. All brands considered here were judged similar on those criteria. In so far as reported quality differences exist, they are on criteria that are not measureable for consumers, such as relative aggression to fabrics. The establishment of the ordering of brands on this criterion necessitates carefully calibrated lab tests on fabric samples.

3. We will later reject the possibility that the inclusion of these variables alters the basis of segmentation.

4. We re-estimated the logit model using only the observations of the in-store sensitive segment in order to derive the elasticities as implied by the logit model. This was done to enable a consistent comparison with the HCSM model, which is a segment specific model.
<table>
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<th>SHARE</th>
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<td>CSM</td>
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<td>loyal segment</td>
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<tr>
<td>Size constant</td>
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<td>25</td>
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</table>

* * significant at 0.075 level
** * significant at 0.05 level
*** significant at 0.01 level (all one-sided)

b This size constant is fixed at 0.000 to set a metric
### Table 3: Predictive Validation Results

<table>
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<tr>
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<td>Hit-rate estimation</td>
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<td>Hit-rate Hold-out</td>
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<td>0.715</td>
<td>0.704</td>
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<tr>
<td>ACP estimation</td>
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<td>0.587</td>
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<td>ACP Hold-out</td>
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<td>VCP estimation</td>
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<td>---------------</td>
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<tr>
<td>0.2</td>
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<td>0.5</td>
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</table>

Table 4: Process Validation Results

* * significance (one sided) at 0.1 level
** * significance at the 0.05 level
Figure 1: The distribution of consideration set size in the two segments
Figure 2: Competitive Clout and Vulnerability

(i) As implied by local price response

(ii) As implied by the Logit Model

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In Figure 2(i) the figures in parenthesis indicate the proportion of all purchase occasions that the corresponding brand is predicted to be in the consideration set.
References


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