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The authors develop an approach to reveal segmentation in response to marketing variables at a brand-level perspective. In the proposed procedure, response segmentation is analyzed separately for each brand instead of jointly across all brands. This yields a segmentation picture oriented toward the potential targeting objectives of the brand manager. Using the multinomial logit and probabilistic mixture models, the procedure first calibrates consumer response in the brand choice decision. Individual-level measures of response for a given marketing variable (e.g., price) are then computed, and brand-level segments are obtained by clustering brand-specific response. Using scanner panel data, the approach is applied to price response segmentation for brands that compete in the ground coffee category. The results illustrate a series of implications for brand strategy, particularly the potential for targeting marketing activity to different response segments.

A Brand's Eye View of Response Segmentation in Consumer Brand Choice Behavior

A critical function of marketing research is to inform managers of customer segmentation relevant to decision making in their markets. Researchers working with scanner panel data have recently used probabilistic mixture models to reveal post hoc segmentations in household purchase behavior (e.g., Bucklin and Gupta 1992; Grover and Srinivasan 1987; Kamakura and Russell 1989).

The extensive disaggregate data in scanner panels have permitted investigators to effectively base segmentation schemes on differences in revealed choice behavior. A common feature of these approaches is a picture of segmentation taken at the product category level. For example, Grover and Srinivasan's (1987) procedure groups households according to their switching behavior across brands. Working in the multinomial logit framework, Kamakura and Russell (1989) group households on the basis of choice response across brands, and Bucklin and Gupta (1992) group households on the basis of commonality in response function parameters across brands.

From a managerial viewpoint, these procedures can provide important diagnostic information on the customer-driven basis for intracategory brand competition and competitive market structure. However, the category-level orientation of these results means that the brand manager does not get an immediate picture of the segmentation in response behavior *specific to his or her brand.*

Building on previous research, we investigate this problem using the disaggregate multinomial logit modeling framework (Guadagni and Little 1983) and its multisegment extension (e.g., Kamakura and Russell 1989).

The logit model captures response as a function of both intrinsic preference *and* the household's sensitivity to a particular marketing activity (e.g., price, promotion, or advertising). Because the logit assumes market response follows an S-shaped curve, a household's reaction to, for example, a price change on a strongly preferred brand will be smaller than its reaction to a price change on a moderately preferred brand. A strong preference places the household's starting choice probability on the flatter, top portion of the curve, whereas a moderate preference puts the starting point on the steeper, middle portion of the curve. This nonlinear response produces *brand-specific* price sensitivity at the individual level. We believe it also has important implications for market segmentation.

We develop and illustrate a new approach to response segmentation that organizes results at the brand level—what we call a "brand's eye view" of the market. The goal is to build on existing procedures to represent response heterogeneity in a more strategically compelling way to the brand manager.

Rather than presenting a segmentation picture for the category as a whole, the output from our procedure presents a picture that is specific to a single brand at a time. For exam-

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ple, a category-level segmentation may suggest that 50% of consumers are very price sensitive and the other 50% are price insensitive. A brand-level segmentation, however, may imply that whereas 80% of consumers are very price sensitive to brand A, only 20% of consumers have a high price sensitivity toward brand B. Our approach is designed to permit a brand manager to identify targeting opportunities at this brand-specific segment level.

Our approach uses the multinomial logit model of brand choice to represent choice response behavior. We utilize a probabilistic mixture model, also known as a latent class model, to accommodate heterogeneity in model parameters. The procedure produces a matrix of household-level response measures for own- and cross-effects for all brands in the product category.

We illustrate the application of the procedure to price response, noting that a similar methodology can be used to study other marketing variables. We then take the own- and cross-price response measures pertaining to a single brand and use that vector as the basis for our response segmentation. A cluster analytic procedure ultimately yields the brand-specific response segments and their memberships.

Using scanner panel data, we present an illustrative application of the method to brand choice response in ground caffeinated coffee and discuss the implications for brand strategy. This representation of brand-specific response is likely to be best suited to categories, like coffee, where the brand choice decision accounts for most of the variation in brand sales.

PROPOSED SEGMENTATION APPROACH

Our approach to brand-level response segmentation is based on individual-level own- and cross-price response slopes. These slopes are in turn functions of response coefficients *and* choice probabilities. To provide estimates for these coefficients and probabilities we utilize the multinomial logit choice model and its extension into multisegment mixtures (e.g., Bucklin and Gupta 1992; Kamakura and Russell 1989).

After the logit models have been calibrated, household-level own- and cross-price response measures are computed. The response measures that are specific to each household and each brand provide the basis for the brand-specific response segmentation.

A cluster analysis on the response measures yields the ultimate segmentation scheme. The potentially differing characteristics of the segments can be explored using a variety of demographic, psychographic, and purchase behavior variables.

Logit Choice Model

In the multinomial logit framework, the probability that household h selects brand i at occasion t, given a category purchase, is written as

$$P_t^h(i) = \frac{\exp(U_{it}^h)}{\sum_k \exp(U_{kt}^h)}, \tag{1}$$

where the deterministic component of utility is

$$U_{it}^h = u_i + \boldsymbol{\beta} \mathbf{X}_{it}^h. \tag{2}$$

The parameter u_i is an intercept for brand i, and $\boldsymbol{\beta}$ is a vector of coefficients for variables $\mathbf{X}_{it}^h$. Both marketing variables (e.g., price and promotion) and household-specific variables (e.g., brand loyalty) are included in the $\mathbf{X}_{it}^h$ vector. Here, all households share the same parameter vector $\boldsymbol{\beta}$. Because the model is conditional on category purchase, the subscript t indexes each household's choice occasions over time.

Probabilistic Mixture Model

The basic multinomial logit choice model accommodates heterogeneity in brand preference across households through household-specific variables for brand loyalty. Panelists, however, are still assumed to share common response coefficients for marketing variables like price and promotion. To relax this assumption, our approach calls for the estimation of a probabilistic mixture model that incorporates heterogeneity in response parameters. The mixture model we use here is technically similar to the clusterwise logit model developed by Kamakura and Russell (1989) and the brand choice component of the segmentation work reported by Bucklin and Gupta (1992).

In the multisegment mixture model, a brand's choice probability is a mixture of the choice probabilities from each underlying segment:

$$P_t^h(i) = \sum_{s=1}^{S} \pi_s P_{st}^h(i) \tag{3}$$

where

π_s = share of the sth choice segment, $0 < \pi_s \leq 1$, $\sum_s \pi_s = 1$, and $P_{st}^h(i)$ = choice probability for household h in segment s.

The segment-level choice probability may be written as

$$P_{st}^h(i) = \frac{\exp(U_{it}^h \mid s)}{\sum_k \exp(U_{kt}^h \mid s)}, \tag{4}$$

where $U_{it}^h \mid s$ is utility based on the response parameters specific to segment s. The deterministic portion of utility within segment s is

$$U_{it}^h \mid s = u_{is} + \boldsymbol{\beta}_s \mathbf{X}_{it}^h. \tag{5}$$

Note that the $\boldsymbol{\beta}_s$ vector differs across segments, accommodating heterogeneity in response parameters as well as heterogeneity in the brand loyalty coefficient. A final step applies Bayes' rule to household-specific likelihoods and segment shares (π_s's) to obtain an estimate of each household's probability of belonging to segment s, which we label w_s^h.

The segments produced by the mixture model procedure are still category-level not brand-specific in their orientation. We use this initial category-level segmentation to produce better estimates of choice probabilities and response parameters than would typically be obtained from a single segment approach, as in Guadagni and Little (1983). Thus far, the goal is to produce the best possible *inputs* to the part of the procedure that forms the brand-specific segments.

Response Measures

Our measure of consumer response to price is defined as the rate of change in a given household's choice probability due to a change in price. This measure may be thought of as the slope (or first derivative) of the household's response curve. Each household will have a matrix of response values corresponding to the own- and cross-price effects of each brand in the category. We call this matrix $\mathbf{R}^h$ and calculate it using a simulation approach in which a brand's price is changed by the same fixed amount (e.g., 1%) on every purchase occasion for the household. "Arc slopes" are then computed from the formulas

$$R_{ii}^h = \frac{1}{T_h}\sum_t \frac{(\Sigma_s w_s^h P_{st}^{h'}(i) - \Sigma_s w_s^h P_{st}^h(i))}{(X'_{it} - X_{it})} \text{ and} \tag{6}$$

$$R_{ij}^h = \frac{1}{T_h}\sum_t \frac{(\Sigma_s w_s^h P_{st}^{h'}(i) - \Sigma_s w_s^h P_{st}^h(i))}{(X'_{jt} - X_{jt})}, \tag{7}$$

where T_h is the number of purchase occasions for household h, $P_{st}^{h'}(i)$ is the new choice probability resulting from the price change $X'_{it} - X_{it}$, and w_s^h is the household's updated probability of segment membership. The probabilistic assignment of households to the various mixture model segments (according to $\{w_s^h\}$) implies that the effective price response parameter for a given household is a convex combination of the price coefficients from each segment. Because brand preferences are also likely to differ across the latent segments, this induces a degree of brand-specific heterogeneity into the price coefficient at the individual level.

Determining Brand-Specific Response Segments

The response matrix estimated for each household provides the basis for the proposed segmentation approach. Because we are interested in response segmentation from the perspective of each brand, the unit of analysis becomes the row- or column-vector of response matrix elements corresponding to each brand. We then cluster households on the basis of the similarity in brand-specific response vectors, which we label $\mathbf{R}_i^h$. The response vector incorporates own-price response as well as cross-price responses. Thus, the segmentation is based on both own- as well as cross-price response for the brand in question.

By definition, the elements of the brand response vector $\mathbf{R}_i^h$ will add up to zero, that is, $\Sigma_j R_{ij}^h = 0$, and be correlated with each other. Instead of using these raw response vector elements as the basis for our cluster analysis, we first perform principal components and compute factor scores. This translates the informational content of each household's n-element response vector into n – 1 factor scores, thereby ensuring that the inputs to the cluster analysis will be uncorrelated. After clustering the households by their factor scores, we return to the response vectors $\mathbf{R}_i^h$ to compute mean response levels for each cluster.

The above procedure (principal components, factor scores, and cluster analysis) may then be repeated for each brand in the product category. Because the cluster analysis is within brand, there is no requirement that each brand have the same number of response segments (e.g., segmentation for brand A may best be described with two groups, whereas segmentation for brand B may best be described with four groups). The procedure ultimately produces a distinct set of response segments for *each brand* the investigator wishes to analyze.

APPLICATION

Data

The data are drawn from the Information Resources, Inc. (IRI) coffee scanner panel for Pittsfield, Massachusetts. We focused on the ground caffeinated coffee purchases of 376 randomly chosen households (among those who were ground caffeinated users) over an 84-week period. We divided the data into 32 weeks for initialization of model variables and 52 weeks for calibration of model parameters. A total of 4985 choices were made in the calibration period. Our analysis included the four largest selling brands in the one-pound size, which together accounted for more than 80% of category volume. Their market shares as a percentage of the four-brand total and average selling prices are given below:

Brand	*Market Share*	*Average Price*
Hills Brothers	13.8%	\$2.32
Folgers	30.5	2.36
Maxwell House	28.9	2.50
Chock Full O' Nuts	26.8	2.22

The IRI data set also contains demographic variables describing each household that permit us to illustrate a posterior analysis of response segment characteristics. An important feature of the ground coffee category is its very low proportion of multiunit purchases. Researchers have previously found that consumers' brand choice decisions account for most of the impact of price on brand sales in this category (Chiang 1991; Gupta 1988), suggesting that our choice-based approach to segmentation is appropriate for these data.

Choice Model Specification

The deterministic portion of consumer utility, U_{it}^h, is modeled as follows:

$$U_{it}^h = u_i + \beta_1 BL_i^h + \beta_2 LBP_{it}^h + \beta_3 PRICE_{it} + \beta_4 PROMO_{it}, \tag{8}$$

where:

u_i = constant for brand i, to be estimated,

BL_i^h = loyalty of household h to brand i,

LBP_{it}^h = 1 if i was last brand purchased, 0 otherwise,

$PRICE_{it}$ = actual shelf price of brand i at choice occasion t,

$PROMO_{it}$ = binary indicator variable denoting the promotional status of brand i at occasion t, and

$\beta_1 ... \beta_4$ = parameters to be estimated.

Brand loyalty is computed as the within-household market share of each brand during the initialization period. BL_i^h is designed to capture cross-sectional heterogeneity in choice probabilities. The indicator variable for last brand

Table 1
RESULTS OF MIXTURE MODEL PARAMETER SEGMENTATION[a]

Parameter	Segment 1	Segment 2	Segment 3
β_1 (Brand Loyalty, BL^h_i)	4.440	1.387	.137
	(16.20)	(8.14)	(.37)
β_2 (Last Brand Purchased, LBP^h_{it})	.958	.474	2.743
	(7.00)	(4.99)	(9.69)
β_3 ($PRICE_{it}$)	–.802	–1.729	–.560
	(–3.96)	(–11.78)	(–1.11)
β_4 ($PROMO_{it}$)	3.030	4.753	1.649
	(15.31)	(23.71)	(5.37)
α_1 (Hills Brothers)	.150	.257	–.992
	(.60)	(1.89)	(–2.60)
α_2 (Folgers)	.255	.696	.415
	(1.34)	(5.45)	(1.35)
α_3 (Maxwell House)	.544	.098	.405
	(2.66)	(.59)	(1.30)
π_s (Segment Share)	.30	.64	.06

[a]Asymptotic t statistics in parentheses.

purchased, LBP^h_i, is designed to capture purchase event feedback in choice probabilities.

Our household-level utility model includes the effects of two marketing variables: price and the presence or absence of nonprice promotional activity. We measure price ($PRICE_{it}$) as the actual shelf price of the brand, including temporary discounts, in dollars per unit. We measure promotional activity ($PROMO_{it}$) using an indicator variable set equal to one if the brand is featured or displayed at occasion t and set equal to zero otherwise.

The specification of the multisegment mixture version of the choice model involves the same variables as in Equation (8), but it permits the parameters of the household utility function to be heterogeneous across segments. The deterministic portion of utility, given that the household belongs to segment s, is given by

$$(9) \qquad U^h_{it} \,|\, s = u_i|_s + \beta_{s1}BL^h_i + \beta_{s2}LBP^h_{it} + \beta_{s3}\,PRICE_{it} + B_{s4}\,PROMO_{it},$$

where $\{u_i|_s\}$ and $\beta_{s1}...\beta_{s4}$ are parameters specific to choice segment s.

Choice Model Calibration

We calibrated the single-segment choice model of Equation (1) and then fit multisegment mixture models for two, three, and four segments (Equation 3). The calibration period log likelihoods (LL) of the single-segment and multisegment models are given below:

Number of Segments	*Number of Parameters*	*LL*	*BIC*
1	7	–2,605.4	–2,635.2
2	15	–2,346.2	–2,410.1
3	23	–2,228.9	–2,326.8
4	31	–2,197.8	–2,329.8

We use the Bayesian Information Criterion (BIC) to guide the selection of the number of segments to retain (Bucklin and Gupta 1992). In this case, BIC is minimized for the three-segment solution. After inspecting the four-segment results, in which two segments were quite small, we settled on the three-segment solution.

The parameter estimates for the three-segment model are reported in Table 1. A look at the parameter estimates across the segments shows considerable variation in the importance of brand loyalty as well as sensitivity to price and promotion. The price coefficient for segment 3, for example, is not statistically different from zero. (Our subsequent computations use the estimate; i.e., we did not substitute in zero.)

Computation of Response Slopes

The next phase of the procedure is to compute the set of $\mathbf{R}^h$ matrices of response slopes for all households in the sample. For each household, we use average market conditions to calculate choice probabilities at each purchase occasion. We then lower the price of one brand by 1%, compute the absolute change in choice probabilities for each brand at each occasion, then average over purchase occasions to obtain one column vector of the household's response matrix. We then repeat the procedure across the remaining brands, producing the respective column vector each time.

Segmentation Results

Proceeding brand by brand, we performed principal components analysis on the household response vectors and computed factor scores. We then used these three-element vectors as inputs into cluster analysis. Cluster analysis was conducted using the FASTCLUS procedure in SAS. (FASTCLUS is based on a k-means algorithm.) For each brand, we computed solutions from two to nine clusters and selected the number of clusters for retention using the Cubic Clustering Criterion, which is recommended by SAS for use with the FASTCLUS algorithm. The five-cluster solution was indicated for each brand, with the exception of Hills Brothers, where the four-cluster solution was indicated.

Within each brand, once the number of clusters and household membership were determined, the brand-specific response segmentation could be represented by computing the mean response vector for each cluster. In tables 2a–2d, the first four rows report the mean of the response vector for the households assigned to each response segment for each brand. To highlight the structure of the brand-based response segmentation, we have underlined the mean cross-price response slopes with values greater than or equal to 0.1. The last column reports the mean response for the entire sample.

Each brand has a low-response segment in which the price responsiveness is relatively low for both own- and cross-effects. These segments range from 27% to 38% of the households. By comparison, the mixture model segments reported in Table 1 show the segment with the lowest price coefficient to have only 6% of the market. This highlights a key distinction between the category-level segmentation, as represented in Table 1, and the brand-specific segmentation, as represented in tables 2a–2d. Because many households have high- or low-baseline choice probabilities for specific brands, placing them on the flatter portion of the S-curve, their *brand-specific* price response can be small, whereas their category-level response is large.

Another interesting feature can be found in the results for cross-price response. Each brand has segments with moderately high own-price response and relatively high levels of cross-price response for *one other brand*. These are likely to represent households switching among two acceptable brands on the basis of price promotions. Furthermore, each brand (Hills Brothers being the exception) has a segment that is highly responsive in own-price and in cross-price for *multiple* competing brands. These segments represent households switching among more than two acceptable brands. Although the output for each brand is different in many ways, these shared aspects show that the brands face common structures of response segmentation.

Segment Characteristics

From the demographic information contained in the IRI data base, we selected a series of variables that were potentially related to response segmentation. We also constructed several purchase pattern variables that were potentially related to response segment membership. The Appendix provides details on the variables we examined. In the bottom halves of tables 2a–2d, we report the mean values of the descriptor variables for each segment along with the size (number of households) and the share of each response segment. To save space, we report only those variables from the Appendix that showed a statistically significant difference across response segments in the case of at least one brand.

The ability of the various demographic and purchase pattern variables to discriminate segment members is mixed but significant. To assess the overall ability of these descriptors to segment the segments, we conducted a multiple discriminant analysis for each brand. We report the brand-by-brand results for classification accuracy in the table below.

	Percent Correctly Classified			
Method	*Hills Brothers*	*Folgers*	*Maxwell House*	*Chock Full O' Nuts*
Discriminant	52.6%	45.0%	38.8%	47.4%
Random	25	20	20	20
Maximum	33	28	38	29

Following Morrison's (1969) study, we compared the classification accuracy with the random and maximum assignment rules. In each case the percentage of households that was correctly assigned on the basis of the multiple discriminant analysis is higher than would be the case with a random assignment rule or the maximum assignment rule (i.e., assign all households to the largest segment). Interestingly, however, the ability of the descriptor variables to discriminate segment membership varies across brands. Hills Brothers, which has the smallest market share and the fewest brand-specific segments (four versus five for all others) fares the best, whereas Maxwell House fares the worst. This suggests that differences in targeting ability may exist, raising at least the empirical possibility that *targeting clout* may not go hand in hand with conventional notions of brand strength. We speculate that small share brands or private label brands, because they often appeal to a market niche, may sometimes hold an advantage over larger brands in identifying and characterizing their customers.

An examination of the segment means for the descriptor variables shows that the low-response segment for all brands is typically characterized by higher purchase rates, higher income levels, more store loyalty, higher employment levels, and lower deal loyalty than other response segments. Hills Brothers, Folgers, and Chock Full O' Nuts have two or three demographic variables, in addition to purchase behavior variables, that help discriminate low-response segment members from high- or moderate-response segment members. Maxwell House's segments, however, are distinguished only by their purchase behavior variables. This suggests that Maxwell House may have more trouble targeting response segments than its competitors.

BRAND STRATEGY IMPLICATIONS

The output from a brand-specific response segmentation, together with an analysis of segment characteristics, should have a number of potential applications in brand strategy formulation. In this section we briefly discuss several implications and illustrate them with the coffee market application.

Determining Attractive Response Segments

As noted in the previous discussion, each brand has a distinct low-response segment of nontrivial size. Such segments might be targeted, if they are sufficiently identifiable, for less intensive couponing activity. Additionally, trade marketing efforts designed to obtain on-shelf price promotions might be reduced for stores at which these segments shop. (Note that higher levels of store loyalty for these low-response segments may facilitate this.) The high-response segments for Folgers (Table 2b), Maxwell House (Table 2c), and Chock Full O' Nuts (Table 2d) suggest potentially attractive opportunities for targeting more aggressive price-related activity.

Impact of Targeting on Competition

Management may also directly assess a targeting strategy's impact on other brands by examining the cross-effects pattern in the potential target segment. This information would be valuable to manufacturers that have more than one brand in a product class, enabling them to avoid targeting activities that unduly cannibalize the sales of sister brands. Moreover, management can quickly tell whether other segments have a low cannibalization of sister brands and a high impact on competitors' brands. Consider the cases of Hills

Brothers and Folgers. Hills Brothers may find its segment 3 of more interest than segments 1 or 2 if Chock Full O' Nuts has a less reactive history than Folgers or Maxwell House. Segment 3 is also attractive because it is more distinctive in its demographic profile than the others, that is, low income and low female employment. Similarly, Folgers may wish to target its segments 3 or 4, where it has a high impact on only Maxwell House or Chock Full O' Nuts, instead of segment 1 where there is substantial impact on all three competitors.

Predicting a Competitor's Targeting Decisions

Because results are produced for *all* brands in the category, managers may, if they wish, obtain a brand's eye view not only of their own product but of the competition as well. This may permit management to understand and potentially predict the targeting strategies of competitors, in effect psyching out the competition. What makes the brand's eye view important is that each brand's targeting situation *may* differ from its competitors.

Some brands may have distinct and attractive high-response segments (suggesting more aggressive pricing), whereas other brands may have distinct and attractive low-response segments (suggesting less aggressive pricing). For example, Hills Brothers might find its segment 3 attractive for aggressive pricing (highest possible own-price response with demographic identification) and segment 4 attractive for nonaggressive pricing (lowest own-price response with demographic identification). Similarly, Chock Full O' Nuts might find its segment 1 attractive for aggressive pricing and segment 5 attractive for nonaggressive pricing.

Assessing Targeting Clout

The opportunity to target marketing actions to specific brand response segments adds another element to the relative competitive strength of a brand versus its rivals. If competitors' most promising segments are not targetable because they cannot be identified, whereas one's own segment can be, the brand may enjoy a competitive advantage. Indeed, targeting clout, that is, a brand's potential to target its marketing action better than its competitors, may provide a source of competitive strength to otherwise weak brands.

In the coffee application, Maxwell House appears to have a high level of competitive strength when it is defined in the conventional sense. Looking at the impact that Hills Brothers has on competition (Table 2a), Maxwell House appears better insulated across segments than Folgers or Chock Full O' Nuts. Maxwell House also appears relatively well insulated against Chock Full O' Nuts' pricing moves (Table 2d), and it also fares well against Folgers' moves (Table 2b). Overall, Folgers, Hills Brothers, and Chock Full O' Nuts appear consistently more vulnerable to competitive price cuts than Maxwell House. However, Maxwell House may be least able to effectively pursue a targeting strategy, because demographic and purchase variables are poor discriminators of its segment memberships. But Hills Brothers may be able to target its segments 3 and 4, Chock Full O' Nuts its seg-

Table 2a

HILLS BROTHERS RESPONSE SEGMENTATION

	Response Segment				Total Sample
	1	*2*	*3*	*4*	
Response Means†					
$R_{H,H}$	–.258	–.240	–.258	–.053	–.184
$R_{F,H}$	.149	.088	.094	.021	.082
$R_{M,H}$	.048	.099	.040	.014	.046
$R_{C,H}$	.059	.052	.123	.018	.056
Demographic Means‡					
Family Size	3.16	3.25	3.22	3.10	3.18
Income	.31	.42[a]	.24[b]	.46[a]	.37
Male Employment	.68[a]	.75[a]	.70[a]	.80[a]	.74
Female Employment	.29	.31	.19[b]	.35[a]	.29
Category Purchase Behavior Means‡					
Purchase Rate	11.90[b]	9.17[c]	14.74[a]	16.10[a]	13.26
Deal Proneness	.89[a]	.88[a]	.92[a]	.50[b]	.76
Store Loyalty	.61[a]	.67[a]	.53[b]	.67[a]	.63
Means for Purchase Behavior of Hills Brothers‡					
Preference Share	.21[a]	.19[c]	.20[b]	.05[d]	.14
Price Paid	$1.96[a]	$1.96[a]	$1.88[b]	$2.01[a]	$1.95[a]
Proportion Bought on Deal	.91[a]	.95[a]	.95[a]	.79[b]	.91
Segment Information					
Segment Size	91	84	76	125	376
Segment Share	.24	.22	.20	.34	1.00

†$R_{H,H}$ = Hills Brothers's response to Hills Brothers's price;
$R_{F,H}$ = Folgers's response to Hills Brothers's price;
$R_{M,H}$ = Maxwell House's response to Hills Brothers's price;
$R_{C,H}$ = Chock Full O'Nuts's response to Hills Brothers's price.

‡Differently lettered superscripts across segment means denote differences that are significant at the .05 level; segment means with like superscripts are not significantly different from each other; segment means with no superscript are not significantly different from the means that are immediately higher or lower. For example, income in segment 2, .42, is significantly different from segment 3, .24, but neither is significantly different from segment 1, .31.

Table 2b
FOLGERS RESPONSE SEGMENTATION

	Response Segment					*Total Sample*
	1	*2*	*3*	*4*	*5*	
Response Means†						
$R_{F,F}$	−.367	−.325	−.316	−.314	−.059	−.261
$R_{H,F}$	.139	.202	.081	.078	.011	.080
$R_{M,F}$	.099	.049	.158	.057	.024	.084
$R_{C,F}$	.132	.075	.078	.180	.025	.097
Demographic Means‡						
Family Size	3.32^{a}	2.62^{b}	3.09	3.30^{a}	3.09	3.18
Income	.33	.31	.37	.30^{b}	.46^{a}	.37
Male Employment	.74	.44^{b}	.69^{a}	.72	.84^{a}	.74
Female Employment	.20^{b}	.54^{a}	.33	.28	.34^{a}	.29
Category Purchase Behavior Means‡						
Purchase Rate	13.45^{a}	7.77^{b}	10.25^{b}	14.16^{a}	15.90^{a}	13.26
Deal Proneness	.90^{a}	.89^{a}	.84^{a}	.89^{a}	.45^{b}	.76
Store Loyalty	.60	.63	.66^{a}	.54^{b}	.68^{a}	.63
Means for Purchase Behavior of Folgers‡						
Preference Share	.42^{a}	.32^{c}	.37^{b}	.30^{c}	.30^{c}	.35
Price Paid	\$2.04^{c}	\$1.92^{c}	\$2.12^{b}	\$1.98^{c}	\$2.33^{a}	\$2.13
Proportion Bought on Deal	.85^{a}	.91^{a}	.75^{b}	.86^{a}	.30^{c}	.66
Segment Information						
Segment Size	105	13	91	67	100	376
Segment Share	.28	.03	.24	.18	.27	1.00

†$R_{F,F}$ = Folgers's response to Folgers's price;
$R_{H,F}$ = Hills Brothers's response to Folgers's price;
$R_{M,F}$ = Maxwell House's response to Folgers's price;
$R_{C,F}$ = Chock Full O'Nuts's response to Folgers's price.
‡Differently lettered superscripts across segment means denote differences that are significant at the .05 level; segment means with like superscripts are not significantly different from each other; segment means with no superscript are not significantly different from the means that are immediately higher or lower.

Table 2c
MAXWELL HOUSE RESPONSE SEGMENTATION

	Response Segment					*Total Sample*
	1	*2*	*3*	*4*	*5*	
Response Means†						
$R_{M,M}$	−.326	−.238	−.200	−.185	−.091	−.186
$R_{H,M}$	.091	.099	.037	.037	.021	.047
$R_{F,M}$	.150	.084	.128	.057	.039	.085
$R_{C,M}$	.087	.054	.034	.090	.031	.054
Demographic Means‡						
Family Size	3.23	3.16	3.21	3.05	3.19	3.18
Income	.36	.48	.32	.29	.41	.37
Male Employment	.76	.76	.68	.65	.79	.74
Female Employment	.31	.28	.28	.27	.30	.29
Category Purchase Behavior Means‡						
Purchase Rate	11.43^{c}	8.32^{d}	11.30^{c}	13.90^{b}	15.74^{a}	13.26
Deal Proneness	.88^{a}	.87^{a}	.82^{a}	.86^{a}	.62^{b}	.76
Store Loyalty	.62^{a}	.61	.70^{a}	.53^{b}	.64^{a}	.63
Means for Purchase Behavior of Maxwell House‡						
Preference Share	.30^{a}	.26^{b}	.23^{c}	.17^{c}	.26^{b}	.25
Price Paid	\$2.50^{a}	\$2.52^{a}	\$2.51^{a}	\$2.50^{a}	\$2.50^{a}	\$2.50
Proportion Bought on Deal	.83^{a}	.73^{a}	.72^{a}	.78^{a}	.45^{b}	.64
Segment Information						
Segment Size	80	25	66	60	145	376
Segment Share	.21	.07	.18	.16	.38	1.00

†$R_{M,M}$ = Maxwell House's response to Maxwell House's price;
$R_{H,M}$ = Hills Brothers's response to Maxwell House's price;
$R_{F,M}$ = Folgers's response to Maxwell House's price;
$R_{C,M}$ = Chock Full O'Nuts's response to Maxwell House's price.
‡Differently lettered superscripts across segment means denote differences that are significant at the .05 level; segment means with like superscripts are not significantly different from each other; segment means with no superscript are not significantly different from the means that are immediately higher or lower.

TABLE 2d

CHOCK FULL O'NUTS RESPONSE SEGMENTATION

	Response Segment					*Total Sample*
	1	*2*	*3*	*4*	*5*	
Response Means†						
$R_{C,C}$	−.344	−.285	−.241	−.233	−.062	−.208
$R_{H,C}$	.115	.136	.052	.053	.015	.057
$R_{F,C}$	.163	.103	.142	.083	.029	.097
$R_{M,C}$	.069	.046	.046	.097	.020	.054
Demographic Means‡						
Family Size	3.20	2.75	3.34	3.09	3.17	3.18
Income	.18[d]	.32	.34[c]	.41[b]	.49[a]	.37
Male Employment	.67[b]	.73	.74	.70	.82[a]	.74
Female Employment	.22	.30	.29	.31	.32	.29
Category Purchase Behavior Means‡						
Purchase Rate	15.53[a]	9.40[c]	12.61[b]	10.35[c]	15.49[a]	13.26
Deal Proneness	.93[a]	.90[b]	.86[c]	.85[c]	.49[d]	.76
Store Loyalty	.52[d]	.67[b]	.62[c]	.63[b]	.70[a]	.63
Means for Purchase Behavior of Chock Full O' Nuts‡						
Preference Share	.36[a]	.30[b]	.23[c]	.25[c]	.24[c]	.27
Price Paid	\$1.97[c]	\$1.95[c]	\$2.02[b]	\$2.09[a]	\$2.08[a]	\$2.03
Proportion Bought on Deal	.92[a]	.87	.83[b]	.74[c]	.51[d]	.75
Segment Information						
Segment Size	66	20	93	88	109	376
Segment Share	.18	.05	.25	.23	.29	1.00

†$R_{C,C}$ = Chock Full O' Nuts's response to Chock Full O' Nuts's price;
$R_{H,C}$ = Hills Brothers's response to Chock Full O' Nuts's price;
$R_{F,C}$ = Folgers's response to Chock Full O' Nuts's price;
$R_{M,C}$ = Maxwell House's response to Chock Full O' Nuts's price.

‡Differently lettered superscripts across segment means denote differences that are significant at the .05 level; segment means with like superscripts are not significantly different from each other; segment means with no superscript are not significantly different from the means that are immediately higher or lower.

ments 1 and 5, and Folgers its segment 5. Maxwell House managers might take comfort in the probable competitive impact of these targeting scenarios: competitors would cannibalize each other, because Maxwell House has better insulation in each target segment than the other two brands.

CONCLUSION

We have developed and illustrated a new brand-level approach to post hoc segmentation with scanner panel data. Our approach builds on existing models to provide a picture of response segmentation that is directly relevant to the perspective of the brand manager. The results, driven by the actions that the brand controls (e.g., its own pricing moves), should permit managers to readily assess the opportunities for targeting such actions to different customer groups. They also provide an assessment of the segmentation opportunities available to competing brands, allowing one to in effect psych out the competition by examining the marketplace from its perspective.

In designing our approach, we attempted to draw on well-established models and statistical procedures (e.g., the logit model and cluster analysis) but to combine them in such a way as to deliver more focused and informative segmentation pictures to the brand manager.

Existing procedures, such as probabilistic mixture models, have proven to be powerful tools for market analysis. Our view is simply that they stop short of providing important decompositional information about the market *at the brand level*. From the brand manager's perspective, the category-level orientation of existing procedures may not be able to provide all the specific segmentation information needed to assess and design targeting strategies.

We have attempted to illustrate the potential value of our procedure by studying price response in choice behavior for the ground coffee category. The procedure proved effective in identifying a series of potential targeting opportunities for each brand. Although we were limited in the demographic variables available (and had no psychographic information on the households), the analysis of segment characteristics pointed to differences in the actionability of such targeting strategies across brands.

Although the correspondence between purchase behavior and identifiable characteristics is low for most packaged goods, and the coffee category appears to be no exception, we argue that if this correspondence is unevenly distributed across brands, opportunity may exist for some and not for others. Our procedure is designed to assist brand managers in identifying these opportunities and assessing whether competitors share them.

Although this illustrative analysis is clearly limited in scope, the future opportunities for brand managers to target response segments seem promising. As it stands now, an analysis of scanner panel data sets provides results based on a sample of the population. To actually implement targeting strategies, aggregate-level demographic measures pertaining to local areas, such as census tracts, would be used. Encouragingly, Hoch and colleagues (1993) find very strong relationships between the demographics of store trading areas and price sensitivity, suggesting a strong potential for targeting opportunities.

The establishment of shopping clubs by a number of supermarket chains around the country provides another route to response segment targeting. The data collected from these programs amount to chain-level scanner panels, and retailers hope to sell information to manufacturers that are interested in targeting their marketing activity. For example, household-level direct mail campaigns could be designed and implemented from these data sets.

A limitation of our current work is that the response segmentation is determined by studying the brand choice decision. We have chosen to start here because the brand choice decision accounts for most of the impact of price and promotional activity on consumer purchase behavior (e.g., Chiang 1991; Gupta 1988). Our procedure is most appropriate for product categories with purchase characteristics similar to ground coffee, specifically those with a very limited extent of multiunit purchases (e.g., refrigerated orange juice, laundry detergent, household cleaning products, and health and beauty aids).

In product categories where stockpiling behavior is more common, the overall clout of each brand may depend on its position in the choice decision as well as the purchase quantity decision. For example, brands with clout in choice may be vulnerable in quantity (and vice versa). A complete brand's eye view of response segmentation would ultimately include the brand-specific aspects of category expansion. Thus, a key direction for further research is to generalize the concept of a brand's eye view beyond brand choice behavior.

APPENDIX

The variables listed below were used in the analysis of response segment characteristics. Only those variables that yielded significant differences across segments for at least one brand are reported in tables 2a–2d.

Demographic Variables

1. *Family size*. Number of persons in the household.
2. *Income*. Coded 1 if household income was greater than \$25,000 and 0 otherwise (\$25,000 is approximately the sample median).
3. *Age of Male Head of Household*. Coded 1 if over age 45 and 0 otherwise.
4. *Age of Female Head of Household*. Coded 1 if over age 45 and 0 otherwise.
5. *Education of Male Head of Household*. Coded 1 if some college or more and 0 otherwise.
6. *Education of Female Head of Household*. Coded 1 if some college or more and 0 otherwise.
7. *Employment Status of Male Head of Household*. Coded 1 if employed full time and 0 otherwise.
8. *Employment Status of Female Head of Household*. Coded 1 if employed full time and 0 otherwise.

Category Purchase Behavior Variables

1. *Purchase Rate*. Number of purchases of ground caffeinated coffee (among the four brands studied) made during the 52-week calibration period.
2. *Deal Proneness*. Percentage of total category purchases made on promotion.
3. *Store Loyalty*. Herfindahl index of a household's store shares, defined as $\Sigma_j(ss_j^h)^2$, where ss_j^h is the percentage of ground caffeinated coffee purchases household h made in store j.

Brand Purchase Behavior Variables

1. *Preference Share*. Brand's market share under average price conditions and no promotion.
2. *Price Paid*. Average price paid for the brand by a household.
3. *Proportion Bought on Deal*. Percentage of brand purchases made on promotion.

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