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Segmenting consumers using multiple-category purchase data

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Abstract

There is increasing interest in understanding and characterizing the behavior of consumers across multiple categories. In this research we examine insights from segmentation derived from considering consumer behavior in multiple categories jointly. To derive the segmentation we develop a logit-mixture model of brand choice that considers the behavior of customers in multiple categories jointly. When a brand competes in multiple categories we generalize the effect of purchase feedback to include the effect of purchases of the brand in multiple categories. An application using data on purchases made by a panel of consumers in three baby products categories, two of which contain some common brands, is presented. We discuss the insights from deriving segmentation in which multiple categories are considered jointly and the implications of our results for a manager whose brand competes in more than one category. Our results should also be of interest to a manager of a brand that is marketed only in a single category yet competes against multiple-category competitors.

Keywords: Segmentation; Multi-category; Brand choice; Mixture models; Logit models

1. Introduction

The steps in target marketing are well documented (e.g., Kotler, 2000): market segmentation in which segmentation variables are identified, the market is segmented, and profiles of the resulting segments are developed; targeting, which involves evaluating the attractiveness of each segment and selecting the segment(s) to target; and, positioning, in which alternative positioning concepts are evaluated and the chosen concept is implemented.

The process presents challenges to managers when the same brand name is used in multiple categories. Desired consistency in brand associations (e.g., Aaker, 1996; Keller, 1998) has implications for the extent to which a positioning strategy for a given brand can be developed independently for each category. The degree to which a segmentation transcends category boundaries is therefore a useful input for managers developing and implementing a positioning strategy for brands that compete in multiple categories. Knowledge of the extent to which a segmentation transcends multiple categories is also a useful input for a single-category brand in devising a competitive strategy that takes into account its multiple-category competitors.

In this research, we extend a traditional single-category approach to uncovering segments to one that

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utilizes knowledge of consumers' preferences in multiple categories. A multiple-category perspective provides a richer understanding of the context in which choices are made (Russell et al., 1999). We define a single-category approach as one that segments customers based on an independent analysis of a single category. By analyzing multiple categories jointly, we derive a segmentation in which a given segment is characterized by the preferences and behaviors of its members in a number of categories; a segment definition transcends category boundaries.

The paper proceeds as follows. We first briefly review related prior research. Next, we present our approach for deriving segmentation in which multiple categories are considered jointly. We introduce our data, identify segments, and then profile the segments using available demographic data. A dominant theme in recent research into the choice behavior of consumers is the inclusion of possible dependencies across multiple categories (e.g., Andrews & Currim, 2002; Erdem, 1998; Manchanda, Ansari, & Gupta, 1999; Russell et al., 1997; Seetharaman, Ainslie, & Chintagunta, 1999). The choice model specification generalizes the influence of feedback from prior brand purchases to allow for experiences with a brand in multiple categories. We compare the segmentation derived from utilizing the data on consumers' behavior in a single category with segmentation derived from utilizing data on their behavior in multiple categories jointly. We highlight insights relevant for a manager whose brand competes in more than one category and for a manager of a brand that is marketed only in a single category yet competes against multiple-category competitors. We conclude with a discussion of our results, the contributions of our study and the implications of our findings for research and practice.

2. Background

It is only recently that individual-level analyses of consumer choice behavior have examined multiple categories concurrently. Historically, research in marketing has typically focused on independent analyses of a single category (see Meyer & Kahn, 1991; Wedel & Kamakura, 1999).

For brands competing in multiple categories, the degree of overlap across categories in segments deemed attractive in each category should be of interest. Also of interest is the extent to which behavior is similar across the categories examined. Personality theorists (e.g., Allport, 1975) for example have argued that people are predisposed to certain behaviors and such predispositions are relatively stable. Alternatively, a social cognitive view (e.g., Mischel & Mischel, 1973) suggests that the psychological effect of a situation depends on the person's interpretation of the situation. Differences in interpretation can vary as a function of significant individual and process differences. The former suggests, for example, that intrinsic brand preference and price sensitivity are consumer traits that are relatively stable across categories and time. Consumers who are, say, among the most price sensitive in one category would most likely be among the most price sensitive in another, though the extent of price sensitivity may differ. The latter suggests that no such relationship exists; the effect of context (e.g., Menon & Kahn, 1995; Srivastava, Alpert, & Shocker, 1984) is so strong that generalizing beyond the focal category under study is infeasible.

Multiple-category issues have been reviewed in Russell et al. (1997, 1999), and in a number of recent empirical papers that deal with consumer choice in multiple categories (e.g., Andrews & Currim, 2002; Erdem, 1998; Manchanda et al., 1999; Seetharaman et al., 1999). For brevity, we do not repeat the information contained in those papers. A common theme in multiple-category research is that consumers use information from a number of product categories prior to making a decision, and hence dependencies exist in choice outcomes across categories (Russell et al., 1999). This may be because a consumer's consumption experience with one product affects the choice probabilities of another product sharing say a common brand name (Erdem, 1998; Harlam & Lodish, 1995), or due to a consumer's "inventory" (or portfolio) of products (Kamakura, Ramaswami, & Srivastiva, 1991). Similar to Russell and Kamakura (1997) we are interested in multiple category brand preference. They look for the existence and nature of cross-category correlations in brand preferences. Different from that study, we are interested in characterizing segments based on their brand preferences and responsiveness to marketing actions in multiple categories. We do not seek general guidelines for various brand types, but instead show how considering multiple categories jointly can be used to identify market opportunities.

3. Empirical analysis

We identify segments using the latent class or mixture modeling extension (Kamakura & Russell, 1989) of the single-segment multinomial logit framework. We first discuss a traditional single-category approach that utilizes information only from a single focal category. Next, we present a multiple-category extension in which the segmentation is derived jointly across categories. Based on available data, preference for a brand is expressed as a function of intrinsic brand preference, purchase feedback, and price.

3.1. Single-category analysis

For a market with S segments, the probability of household h choosing brand i on purchasing occasion t is,

$$P_{it}^{h} = \sum_{s=1}^{S} \pi_s P_{ist}^{h} = \sum_{s=1}^{S} \pi_s \frac{\exp(\alpha_{is} + \beta_s X_{it}^{h})}{\sum_{j \in C^h} \exp(\alpha_{js} + \beta_s X_{jt}^{h})} \qquad (1)$$

where, π_s is the share of the sth segment ($0<\pi_s<1$, $\Sigma\pi_s=1$), P_{ist}^{h} is the probability that household h in segment s buys brand i on purchase occasion t, α_{is} is the intrinsic utility of brand i for segment s, X_{it}^{h} is a vector of marketing variables and household-specific characteristics, β_s is a vector of segment-specific parameters for variables X_i^{h}, and C^h is the choice set faced by household h. The likelihood of an observed choice history H^h for household h can be computed as,

$$\begin{aligned} L(H^h) &= \sum_{s=1}^{S} [\pi_s L(H^h \mid s)] \\ &= \sum_{s=1}^{S} \left[\pi_s \prod_{t} \left(\prod_{i \in C_h} (P_{ist}^{h})^{d_{it}^{h}} \right) \right] \end{aligned} \qquad (2)$$

where, d_{it}^{h} is an indicator that household h chose brand i on purchase occasion t. To facilitate estimation we define $\pi_s = \exp(\lambda_s)/\sum_{s'} \exp(\lambda_{s'})$. The number of observable segments is specified prior to estimation and then compared to alternative specifications using appropriate fit statistics.

3.2. Multiple-category analysis

To extend the single-category model to allow for purchasing in multiple categories, we introduce k to Eq. (1) to denote the category from which a purchase is made. For a market with S segments, the probability of household h choosing brand i when purchasing from category k on occasion t is,

$$\begin{aligned} P_{ikt}^{h} &= \sum_{s=1}^{S} \pi_s P_{ikst}^{h} \\ &= \sum_{s=1}^{S} \pi_s \frac{\exp(\alpha_{iks} + \beta_{ks} X_{ikt}^{h})}{\sum_{j \in C_k^h} \exp(\alpha_{jks} + \beta_{ks} X_{jkt}^{h})}. \end{aligned} \qquad (3)$$

We conjoin the purchase strings from each category. Each segment is characterized by its behavior in *all* categories under study jointly. Using the observed choice history from each of the k categories for household h, H_k^h, the likelihood of an observed conjoined choice history H^h can be computed as,

$$\begin{aligned} L(H^h) &= \sum_{s=1}^{S} \left[\pi_s \prod_{k} L(H_k^h \mid s) \right] \\ &= \sum_{s=1}^{S} \left[\pi_s \prod_{k} \left(\prod_{t} \left(\prod_{i \in C_k^h} (P_{ikst}^{h})^{d_{ikt}^{h}} \right) \right) \right] \end{aligned} \qquad (4)$$

As with the single-category approach, the number of observable segments is specified prior to estimation and then compared to alternative specifications using appropriate fit statistics.

3.3. Model parameters

Based on available data, we specify the utility for a brand as a function of intrinsic brand preference, purchase feedback, and price. We allow for household purchasing dynamics through the inclusion of the user's age as a covariate.

3.3.1. Purchase feedback

Purchase feedback refers to the impact of past purchases on current preferences (Ailawadi, Gedenk, & Neslin, 1999). Ailawadi et al. (1999) report that the two most common approaches to purchase feedback methods in marketing are an indicator of the brand purchased at the last purchase occasion (*LBP*) and an exponentially smoothed measure of previous purchases (*GL_LOY*) (Guadagni & Little, 1983). We use *LBP*. In a mixture modeling framework such as that used here, Ailawadi et al. (1999) found that segments derived using *LBP* are more stable than those derived using *GL_LOY*. Furthermore, *LBP* is not sensitive to the length of the purchasing history, and its inclusion allows the separation of temporal from cross-sectional effects (Heilman, Bowman, & Wright, 2000). We capture cross-sectional heterogeneity via latent classes versus a separate term calibrated on an initialization period (Bucklin & Gupta, 1992). The substantive conclusions presented below do not change if *GL_LOY* is used instead of *LBP*.

Traditionally when examining a single category in isolation, purchase feedback is included as being due only to prior purchases of the brand within the focal category. In a multiple-category context, a consumer's consumption experience with a product affects the choice probabilities of another product sharing a common brand name (e.g., Erdem, 1998; Harlam & Lodish, 1995). Defining LBP_k as an indicator of the last brand purchased in category k, we extend the single-category approach to allow for purchase feedback effects from multiple categories. In general,

$$\textit{Purchase Event Feedback} = f_s(LBP_{ik_1t},\ LBP_{ik_2t},\ldots) \quad (5)$$

For the case of two categories, k_1 and k_2, for exposition we specify a main effect and the interaction term,

$$\beta_{1s}LBP_{ik_1t} + \beta_{2s}LBP_{ik_2t} + \beta_{3s}(LBP_{ik_1t}\times LBP_{ik_2t}) \quad (6)$$

This specification nests a number of alternative influences of purchase feedback in a multi-category setting including an effect due only to purchases in the focal category (β_{2s}, $\beta_{3s}=0$), separate-effects-only for the focal category and for other categories in which the brand is available ($\beta_{3s}=0$), and a moderating-only effect of purchases from categories other than the focal one ($\beta_{2s}=0$).

Two approaches to studying cross-category relationships are: (a) response parameters may be correlated across categories, and (b) previous or concurrent choices may impact the current choice.[2] In this paper, we focus on the effect of previous choices on the current choice.

3.3.2. Incorporating household purchasing dynamics

Because we examine the purchases made by mothers in the baby products category for a specific baby, the baby's age is an observable measure related to time spent purchasing and using products in these categories and is an upper bound for time spent in the category for the specific baby under study. Time spent purchasing and using products in a category has a direct influence on category knowledge (Alba & Hutchinson, 1987). In general, we allow the parameters in the choice model to vary with the baby's age.

$$\alpha_{iks}(t),\ \beta_{ks}(t) = g_s(Age_t^h) \quad (7)$$

We realize that the age of the baby does not capture differences in purchasing frequency across households or over time within a household. However, for the data used in this study, an examination of purchase frequency across households and over time indicates only small variation in purchase frequency across households for a given age of a baby, but a decrease in purchase frequency as a baby grows older.

For exposition, we specify a nonlinear monotone effect of *Age*, and later test this against alternative linear, and non-monotone specifications.

$$\alpha_{iks}(t) = \alpha_{iks0} + \alpha_{iks1}\ln(Age_t^h)$$

$$\beta_{ks}(t) = \beta_{ks0} + \beta_{ks1}\ln(Age_t^h) \quad (8)$$

We do not include an error term and hence implicitly assume that any (managerially relevant) time-varying aspects are captured by the child's age.[3]

[2] We thank a reviewer for pointing this out.

[3] We thank a reviewer for pointing this out.

3.3.3. Choice model specification

Following from the preceding discussion, the utility specification for household h purchasing in category k_1 on occasion t when purchasing from two categories is considered is therefore,

$$\begin{aligned}
U^h_{ik_1st} = {} & \alpha_{0ik_1s} + \alpha_{1ik_1s}\ln(Age^h_t) + \beta_{01k_1s}(LBP^h_{ik_1t}) \\
& + \beta_{11k_1s}(LBP^h_{ik_1t}) \times \ln(Age^h_t) \\
& + \beta_{02k_1s}(LBP^h_{ik_2t}) + \beta_{12k_1s}(LBP^h_{ik_2t}) \\
& \times \ln(Age^h_t) + \beta_{03k_1s}(LBP^h_{ik_1t} \times LBP^h_{ik_2t}) \\
& + \beta_{13k_1s}(LBP^h_{ik_1t} \times LBP^h_{ik_2t}) \times \ln(Age^h_t) \\
& + \beta_{04k_1s}(Price^h_{ik_1t}) + \beta_{14k_1s}(Price^h_{ik_1t}) \\
& \times \ln(Age^h_t) + \varepsilon^h_{ik_1st} \qquad (9)
\end{aligned}$$

α_{0ik_1s} = intrinsic brand utility of brand i in category k_1 for segment

$s\alpha_{1ik_1s}$ = component of intrinsic brand utility of brand i in category k_1 for segment s that varies over time

$\ln(Age_t{}^h)$ = log of the baby's age at purchase occasion t for household h

LBP_{ikt} = last brand purchased in category k; 1 if household h purchased brand i on the most recent purchase from category k, 0 otherwise

β_{01k_1s}, β_{02k_1s}, β_{03k_1s} = baseline effects of last brand purchased in categories k_1, k_2, and their interaction, respectively, for segment s

β_{11k_1s}, β_{12k_1s}, β_{13k_1s} = dynamic effect of last brand purchased in categories k_1, k_2, and their interaction, respectively, for segment s

$Price^h_{ik_1t}$ = price of brand i in category k_1 at purchase occasion t

β_{04k_1s} = baseline effect of price in category k_1 for segment s

β_{14k_1s} = dynamic effect of price in category k_1 for segment s.

Single-category analysis simply excludes the effect of purchase event feedback from categories other than the one under study.

3.4. Posterior household assignment

The above describes the approach to segmenting the customers. Given the model estimates and visibility of the actual purchasing history of each consumer, posterior probabilities of membership to segment s are obtained using

$$w^h_s = \frac{L^h_s}{\sum\limits_{s=1,2,\ldots,S} L^h_s} \qquad (10)$$

where, $L_s{}^h$ is the likelihood of household h's purchasing history given membership to segment s. Each household has a vector of posterior probabilities such that $\sum_{s=1,2,\ldots,S} w^h_s = 1$. Logistic regression is used to determine if the available demographic characteristics of the consumers (to be discussed in the next section) are useful in profiling the resulting segments (Kamakura & Russell, 1989):

$$\ln\left(\frac{w^h_s}{1-w^h_s}\right) = b_s Z^h + e^h_s \qquad s = 1,2,\ldots,S \qquad (11)$$

where Z^h is a vector of characteristics for household h, and b_s is a vector of parameter estimates on those variables. Eq. (11) specifies a separate regression for each segment, estimated using the seemingly unrelated regression procedure.

4. Data

We desire data on the purchasing behavior of customers who make purchases from a number of categories in which the products are not substitutes. We use data from Dympanel's (Spanish subsidiary of the French market research company Sofres) baby products diary panel. The panel tracks purchases made for a specific baby in a household. Purchases from three categories were available: disposable diapers, baby towels, and baby formula. Diapers and towels have common national brands allowing us to compare segmentation results from categories that share common national brands with categories that do not.

The categories are typically stocked together in a store, though they are not substitutes. Qualitative data from a convenience sample of parents suggests that the products could be characterized as weak compliments. We use the terminology "weak" as they are often purchased together, but different from say cake and frosting (Russell et al., 1997), as they can be "consumed" independently.

We examined which categories were purchased together. In 11.6% of the weeks observed, consumers made purchases for both diapers and towels (in that same week, but not necessarily on the same day), in 19.9% of the weeks observed consumers purchased both diapers and formula, in 10.9% of the weeks observed, towels and formula were purchased in the same week, and in 5.0% of the weeks observed, consumers purchased all three products. The fact that the highest purchase coincidence occurs for diapers and formula makes sense given these two products have approximately the same inter-purchasing cycles, whereas towels are bought less frequently (as discussed below).

Competing arguments could be made regarding which cross-category choices we would expect to be more related. Given diapers and formula have approximately the same purchasing cycle and are purchased more often in the same weeks than are towels and diapers or formula and diapers, we might expect the choice relationship across these two categories to be the greatest and hence there could be much gained from considering these two categories jointly. On the other hand, one could argue that because diapers and baby towels are two products used in the same consumer act (i.e., changing diapers), it would make more sense for the choice relationship across these two categories to be the greatest.

The panelists are all mothers. Upon joining, they provide a number of demographic descriptors including their social class status, geographical location, working status, gender of the child and whether or not this is their first child. For the panelists studied here, these factors remained constant over the observation window. Panelists also provide their age and the age of the child when they joined the panel. Discussions with the data provider indicated that consumers in these categories (in this geographic market at least) almost always begin using these products upon the birth of the child. Hence, the age of the child has the appealing feature that it is the upper bound on the time spent purchasing in the category for the child under study. Weekly diary entries record brand purchased, prices paid, and type of outlet where each purchase was made. The observation window for the available data began in January 1992 and continued until December 1995. The mean interpurchase time was 12 days for a diaper purchase, 18 days for a purchase from the towel category, and 11 days for formula purchases.

We retained only those panelists who recorded purchases in all three categories. Panelists can join or exit the panel at any time. For estimation and validation, we retained those panelists who made at least 25 purchases in each of the three categories. A comparison of the panelists used in the analysis with those dropped failed to reject significantly different demographic characteristics. For estimation, we took an 80% random sample to obtain 397 panelists for the estimation sample. One hundred panelists were held out for validation.

Table 1 provides household demographics and summary purchasing statistics for the sample used for estimation. Twenty-six percent of the consumers in the sample worked full-time, 63% reported being of upper or upper-middle class, 65% were first-time moms, 21% reported living in the Madrid or Barcelona metropolitan area, and 52% of the infants were boys.

Panelists were presented with 11 brands from which to record their brand of disposable diaper purchased, 19 brands to record the brand of towels purchased and 10 brands from which to record a

Table 1
Sample characteristics

Characteristic	
Working mom	26%
Mom's age	29.7 years
Upper class	63%
First time mom	65%
Urban	21%
Gender = Boy	52%
Mean interpurchase time:	
Diapers	12 days
Towels	18 days
Formula	11 days

formula purchase. All categories contained one brand labeled as "other" among those mentioned above. Brands in the diaper, towel and formula category were collapsed into six, seven, and seven brands, respectively, based on market share and in a manner that preserved the common brands across the categories. Table 2 shows the average choice share, market penetration, and unit price for the brands used in this analysis.

The market leaders in the diaper, towel and formula category had 35.9%, 37.6% and 38.9% market share, respectively. We label these the "big" or leading national brand and note that this was the same brand in the diaper and towel category. The medium sized brands (three in the diaper and formula category, four in the towel category) ranged in market share from 21.4% to 3.9%. Two of the medium brands (Brands 2 and 3) were identical across the diaper and towel category. The remaining brands were either small market share brands in their respective categories, a composite of "other" brands, or in the case of diapers and towels, a private label brand composite (there are no private label brands in the formula category). These brands are labeled with an "s" in Table 2 to indicate small brands.

To illustrate the insights obtained from considering multiple categories jointly when deriving a segmentation schema versus those obtained from analyzing categories individually, we begin with a traditional single-category analysis for each of the three categories. Each category is analyzed independently and purchase feedback is limited to the effect of prior purchases in that category (referred to as the focal category) only. We use this as a benchmark for comparison to subsequent models that incorporate information from non-focal categories.

Table 2
Summary purchase statistics

	Market share			Penetration			Mean unit price[a] US$[b]/Spanish pesetas		
	Diapers	Towels	Formula	Diapers	Towels	Formula	Diapers	Towels	Formula
Brand 1[c]	35.9 (b)[d]	37.6 (b)	–	94.0	87.4	–	US$0.300/34.39 pts	US$0.040/4.58 pts	–
Brand 2[c]	20.6 (m)	8.8 (m)	–	87.4	52.6	–	US$0.297/34.04 pts	US$0.032/3.67 pts	–
Brand 3[c]	8.0 (m)	3.9 (m)	–	76.1	28.7	–	US$0.249/28.54 pts	US$0.028/3.21 pts	–
Brand 4	15.7 (m)	–	–	70.8	–	–	US$0.246/28.20 pts	–	–
Brand 5	–	9.7 (m)	–	–	62.5	–	–	US$0.028/3.21 pts	–
Brand 6	–	7.3 (m)	–	–	53.4	–	–	US$0.028/3.21 pts	–
Brand 7	–	–	38.9 (b)	–	–	86.6	–	–	US$0.011/1.28 pts
Brand 8	–	–	21.4 (m)	–	–	61.5	–	–	US$0.011/1.29 pts
Brand 9	–	–	13.6 (m)	–	–	51.0	–	–	US$0.011/1.25 pts
Brand 10	–	–	10.7 (m)	–	–	57.7	–	–	US$0.015/1.73 pts
Brand 11	–	–	6.4 (s)	–	–	40.3	–	–	US$0.010/1.19 pts
Brand 12	–	–	4.1 (s)	–	–	30.0	–	–	US$0.012/1.42 pts
PLabel (composite)	12.4 (s)	15.9 (s)	–	63.0	62.5	–	US$0.235/26.94 pts	US$0.017/1.95 pts	–
Other (composite)	7.4 (s)	16.8 (s)	4.9 (s)	50.4	72.8	24.1	US$0.230/26.36 pts	US$0.022/2.52 pts	US$0.001/1.10 pts
	100	100	100						
Sample									
Number of panelists	397	397	397						
Purchases	9925	7863	9810						

[a] One unit in the diaper category was one diaper, in the towel category was one towel, in the milk category was 1 dg.
[b] Converted using the 1993 International Financial Statistics Yearbook (114.62 Spanish pesetas = US$1.00).
[c] Brands 1, 2 and 3 are same in Diaper and Towel Category.
[d] (b) = Big/Leading National Brand, (m) = Medium Sized National Brand, (s) = Small Brand or Private Label Brand (there are no private label formula brands).

We extend the analysis to multiple categories in two stages. First, we simply generalize the utility function from a single-category analysis to incorporate information about past purchases from other categories. The segmentation is still derived at the individual category level. Second, we incorporate information about past purchases from other categories *and* derive the segmentation schema jointly across categories. Table 3 summarizes the model comparisons for the best models among those analyzed.

Table 3
Model comparisons

Category	Model specification						Fit statistics		
	Include child's age	LBP included for			No. of segments (s)	No. of parameters (k)	LL	BIC[a]	Hit rate
		Diapers	Towels	Formula					
Diapers		✓			3	23	− 11,061.10	22,333.87	0.431
(n = 9925		✓			4	31	− 10,984.22	22,253.73	0.453
purchases)		✓			5	39	− 10,965.33	22,289.57	0.442
	✓	✓			2	29	− 10,115.50	20,497.88	0.480
	✓	✓			3	44	− 9,817.22	20,039.36	0.514
	✓	✓			4	59	− 9,763.12	20,069.19	0.504
	✓	✓	✓		3	50	− 9,776.33	20,012.80	0.519
	✓	✓		✓	3	50	− 9,788.20	20,036.54	0.510
	✓	✓	✓	✓	3	56	− 9,743.43	20,002.22	0.528
Towels			✓		3	26	− 11,155.03	22,543.28	0.404
(n = 7863			✓		4	35	− 11,023.57	22,361.09	0.427
purchases)			✓		5	44	− 10,985.43	22,365.54	0.421
	✓		✓		2	33	− 10,720.89	21,737.78	0.462
	✓		✓		3	50	− 10,414.54	21,277.57	0.505
	✓		✓		4	67	− 10,356.21	21,313.41	0.493
	✓	✓	✓		3	56	− 10,394.31	21,290.94	0.519
	✓		✓	✓	3	56	− 10,406.77	21,315.86	0.502
	✓	✓	✓	✓	3	62	− 10,354.43	21,264.98	0.520
Formula				✓	3	26	− 9,986.65	20,212.27	0.398
(n = 9810				✓	4	35	− 9,884.32	20,090.33	0.435
purchases)				✓	5	44	− 9,852.54	20,109.49	0.426
	✓			✓	2	33	− 10,066.25	20,435.80	0.452
	✓			✓	3	50	− 9,763.65	19,986.86	0.485
	✓			✓	4	67	− 9,702.15	20,020.11	0.463
	✓	✓		✓	3	56	− 9,585.88	19,686.46	0.490
	✓		✓	✓	3	56	− 9,585.07	19,684.84	0.494
	✓	✓	✓	✓	3	62	− 9,447.32	19,464.49	0.512
Joint diapers and towels (n = 17,788)	✓	✓	✓		3	104	− 19,581.19	40,180.15	0.539
Joint diapers and formula (n = 19,735)	✓	✓		✓	3	104	− 19,976.34	40,981.26	0.523
Joint towels and formula (n = 17,673)	✓		✓	✓	3	110	− 19,829.45	40,734.68	0.531
Joint diapers,	✓	✓	✓	✓	4	235	− 29,084.06	60,571.11	0.524
towels and	✓	✓	✓	✓	5	294	− 28,510.66	60,027.62	0.538
formula	✓	✓	✓	✓	6	353	− 28,035.42	59,680.44	0.570
(n = 27,598)	✓	✓	✓	✓	7	412	− 27,854.00	59,921.31	0.552

[a] $\text{BIC} = -2(LL - 0.5\ \ln(n)\ k)$.

The models shown in Table 3 are compared on the BIC criterion and the hit rate on the 100 households in the holdout sample. For the cases where the child's age has been included in the model, each variable in the model is allowed to vary with log of the child's age according to Eq. (8). Recall that the baby's age is an observable measure related to time spent purchasing in the category and hence has a direct influence on category knowledge (Alba & Hutchinson, 1987). For those models that include purchase feedback from categories other than the focal one, we report summary fit statistics only for main-effect specifications (β_{03ks}, $\beta_{13ks}=0$ in Eq. (9)), again for parsimony as these specifications fit the data best.

5. Results—segmentation from analyzing categories separately

Beginning with three traditional single-category analyses, one for each category, we find that a three-segment model that captures brand choice as a function of intrinsic brand preference, purchase feedback, and price, where the effect of each varies with the log of the baby's age, fit the data best in each category.

Because the single-category results are each based on data from the same set of consumers, a natural question to ask is the extent to which similarities can be found across the categories using this approach. In instances where a brand competes in multiple categories, developing a unique strategy for a given category is typically avoided for fear of compromising the brand (e.g., Keller, 1998). Even in cases where a brand does not compete in multiple categories, behavior in one category might be useful in predicting behavior in another. For example, one might predict that a consumer who is price sensitive in one category would be price sensitive in all categories. Or a consumer who buys private label brands will be prone to doing so across all categories. Hence, identifying a set or sets of consumers who have similar brand preferences and response to marketing activity in multiple categories is desirable. Table 4 highlights the dominant similarities in segments across the three categories.

In examining brand preferences we see that consumers in Segments D1 (diaper segment 1) and F3 (formula segment 3) show increasing preferences for middle tier and small or lower tier brands over purchasing in the category. The same can be said for consumers in Segments D2 and T3, however, these consumers show an aversion to private label brands as they begin to purchase some of the smaller or lower tier brands later in their purchasing life-cycle. Finally, we see that consumers in Segments T2, F1 and F2 all remain loyal to the top brand in the category regardless of how long they have been purchasing. These results suggest for example that the top national brands may want to focus on consumers in Segments D1 and F3 as these consumers tend to switch away

Table 4
Segment similarities across categories based on parameter estimates when the three categories are analyzed separately

Comparison criterion	Diaper segment(s)	Towel segment(s)	Formula segment(s)	Comment
Intrinsic brand preferences	D1		F3	Increasing preferences for middle and lower tier brands
	D2	T3	NA	Increasing preferences for middle and lower tier brands, except for private label brands
	D3			Indifferent between top tier brands; increasing preferences for middle and lower tier brands
		T2	F1 and F2	Top brand loyal
		T1		Increasing preferences for middle tier brands only
Purchase event feedback	D1 and D3	T2 and T3	F2	Increasing over time
				Decreasing over time
	D2	T1	F3	Stable over time
Price sensitivity			F2	Increasing (more negative) over time
	D1 and D3	T2 and T3		Decreasing (less negative) over time
	D2	T1	F1 and F3	Stable over time

NA = not applicable (no private label in formula category).

from their brands the longer they purchase in the category. The same can be said for consumers in D2 and T3, however, this case would be of special interest to Brand 1 given it competes, and is the leading national brand, in both the diaper and towel categories. Similarly, private label brands might have an opportunity to increase their market shares if they could get consumers in D2 and T3 to purchase their brands. Lastly, all brands in the towel and formula category have the opportunity to steal market share from the leading national brands if they can find a way to make their brands more attractive to consumers in Segments T2 and F1 and F2. While there seems to be some dependencies within consumers across categories that could be leveraged to the advantage of the various brands mentioned above, the ability to capitalize on these dependencies relies on the extent to which the consumers are the *same* across the segments of interest.

Turning to purchase event feedback in the focal category, or "loyalty", we find that consumers in Segments D1 and D3 in the diaper category, T2 and T3 in the towel category and F2 in the formula category, are similar in that the impact of purchase event feedback increases over time. Consumers in Segment D2 for diapers, T1 for towels and F3 for formula are similar in that the effect of purchase feedback is stable over time. Therefore, managers of brands that compete in all three categories, or even two, as do Brands 1, 2 and 3 in the diaper and towel category, might choose to use some type of cross-promotional loyalty program aimed at consumers in Segments D2, T1 and F3 who show no signs of increased loyalties to any brand, regardless of how long they have purchased in the category. Once again, the ability to target these consumers would only be plausible if consumers *common* to D2, T1 and F3 could be easily identified.

Finally, looking at price sensitivity, we find that consumers in Segments D1 and D3 of diapers and T2 and T3 of towels become less sensitive to price the longer they purchase in the respective categories. Therefore, brands competing in both categories should offer price promotions to consumers in the intersection of these segments (i.e., D1 and T2, D3 and T2, D1 and T3, D3 and T3) early in their purchasing histories when they are most responsive to such tactics. On the other hand, price sensitivity for consumers in Segments D2, T1 and F1 and F3 is stable over time, suggesting price promotions can be targeted at these consumers either early or late in the category and have a similar effect.

To exploit similarities in brand preferences and sensitivity to marketing programs across categories, it is necessary to be able to characterize the behavior of a given consumer in each category of interest. A posterior analysis was run to relate available demographic data to each segment to assist in profiling the segments. The variables tested included those shown in the top portion of Table 1 and a variable indicating the percentage of purchases made at discount outlets (40% of all purchases were made at discount outlets). Only those variables that were significant in profiling consumers in a given segment are reported. Table 5 reports the summary results for the intersection of the segments in the diaper category and the towel category, Table 6 reports the results for the diaper category and the formula category and Table 7 reports the results for towels and formula.

The tables each present a three-by-three matrix that cross-classifies households based on their segment membership for two categories. Included are the joint probabilities of being in the intersection of any two segments and the row conditional probability of being in segment *i* of the category on the horizontal axis given membership to segment *j* on the vertical axis. We reject a null hypothesis of independence for the diapers and towels (Table 5; $\chi^2_{df=4}=35.4$; $p<0.01$) and the diapers and formula (Table 6; $\chi^2_{df=4}$=13.4; p<0.01) classification tables suggesting that segment assignments in these pairs of categories are related. We fail to reject a null hypothesis of independence for towels and formula (Table 7; $\chi^2_{df=4}$=5.1; $p<0.75$).

The tables suggest some potentially useful results. As an example, we discussed above that consumers in Segments F1 and F2 in the formula category behave similarly in that both are loyal to the top national brand over their lifetime of purchasing in those categories. From the demographic characteristics reported in Table 7, we see that the characteristic "older moms" is common to all three segments, suggesting that older mothers maintain strong preferences for the leading national formula brands in these two categories regardless of the age of their baby. However, using demographics as a predictor of sim-

Table 5
Summary of segment characteristics and descriptors diapers and towels analyzed separately

			Diaper Category		
			Segment D1 24.9%	Segment D2 39.8%	Segment D 35.3%
		Single-Category Segment Descriptors	Lower Class; Suburbanites; Shops at Mass Merchants	First Time Moms; Younger Moms; Working Full-Time; Lower Class	First-Time Moms; Older Moms; Upper-Class; Urban Dwellers
Towels	Segment T1 32.8%	Older Moms; Lower-Class; Shops at Mass Merchants	6.3%[a] (19.2%)[b]	18.6% (56.7%)	7.9% (24.1%)
	Segment T2 37.0%	First-Time Moms; Younger Moms; Works Full-Time; Urban; Shops at Mass Merchants	7.8% (21.1%)	11.1% (30.0%)	18.1% (48.9%)
	Segment T3 30.2%	Older Moms; Does Not Work Full-Time; Upper-Class; Does Not Shop at Mass Merchants	10.8% (35.8%)	10.1% (33.4%)	9.3% (30.8%)
					100%

[a] Joint Probability.
[b] (Row Conditional) Probability.

Table 6
Summary of segment characteristics and descriptors diapers and formula analyzed separately

			Diaper Category		
			Segment D1 24.9%	Segment D2 39.8%	Segment D3 35.3%
		Single-Category Segment Descriptors	LowerClass; Suburbanites; Shops at Mass Merchants	First Time Moms; Younger Moms; Working Full-Time; Lower Class	First-Time Moms; Older Moms; Upper-Class;Urban Dwellers
Formula	Segment F1 34.3%	Older Moms; Working Full-Time; Girls; Urban Dwellers	6.3%[a] (18.4%)[b]	13.4% (39.1%)	14.6% (42.6%)
	Segment F2 31.7%	First-Time Moms; Older Moms; Does Not Shop at Mass Merchants; Suburbanites	9.6% (30.3%)	10.3% (32.5%)	11.8% (37.2%)
	Segment F3 34.0%	First-Time Moms; Younger Moms; Lower-Class; Shops at Mass Merchants	9.1% (26.8%)	16.1% (47.4%)	8.8% (25.9%)
					100%

[a] Joint Probability.
[b] (Row Conditional) Probability.

Table 7
Summary of segment characteristics and descriptors towels and formula analyzed separately

			Towel Category		
			Segment T1 32.8%	Segment T2 37.0%	Segment T3 30.2%
		Single-Category Segment Descriptors	Older Moms; Lower-Class; Shops at Mass Merchants	First-Time Moms; Younger Moms; Works Full-Time; Urban Dwellers; Shops at Mass Merchants	Older Moms; Does Not Work Full-Time; Upper-Class; Does Not Shop at Mass Merchants
Formula	Segment F1 34.3%	Older Moms; Working Full-Time; Girls; Urban Dwellers	10.8[a] (31.6%)[b]	14.6% (42.7%)	8.8% (25.7%)
	Segment F2 31.7%	First-Time Moms; Older Moms; Does Not Shop at Mass Merchants; Suburbanites	9.3% (29.3%)	11.6% (36.6%)	10.8% (34.1%)
	Segment F3 34.0%	First-Time Moms; Younger Moms; Lower-Class; Shops at Mass Merchants	12.6% (37.0%)	10.8% (31.7%)	10.7% (31.4%)
					100%

[a] Joint Probability.
[b] (Row Conditional) Probability.

ilarities in cross-category brand preference may not generalize. Recall that consumers in Segments D2 and T3 are similar in that they are both averse to private label brands. Looking at Table 5 we find no overlap in the demographic descriptors. In fact, the two segments contradict each other on most demographic variables. D2 is comprised of younger, lower-class moms while T3 is comprised of older, upper-class moms. Consumers in D2 work full-time while consumers in T3 do not. These types of contradictions make it difficult to utilize the apparent synergies across the segments.

Similar ambiguity is evident when looking at price sensitivity. Suppose, for example, that a manager of a brand competing in multiple categories wanted to target price sensitive consumers by running a cross-promotion in both categories. Ideally, this should be directed at consumers whose price sensitivity is at least stable over time rather than those who are becoming less sensitive to price the longer they purchase in the category. This would involve targeting consumers in D2, T1 and F1 or F3. Looking at Table 5, we see that the 18.6% of consumers who are assigned to D2 and T1 are not easily identified. There is no overlap of common demographic variables and furthermore there is the contradiction that consumers in D2 are younger moms while those in T1 are more likely to be older moms. The same can be said for the 13.4% of the consumers in the intersection between D2 and F1. Consumers in D2 are more likely to be younger moms while those in F1 are more likely to be older moms.

Alternatively, if the same manager were trying to identify consumers for which this campaign would be ineffective later in their purchasing cycle (i.e., consumers with decreasing sensitivity to price over purchases), then he/she may look to consumers in D1 and D3 as well as those in T2 and T3. Examining the 7.8% of consumers in the intersection between D1 and T2, it would appear that these consumers shop at mass merchants. However, the descriptors for T3, also a segment of consumers who become less sensitive to price with their baby's age, suggest these consumers do not shop at mass merchants. Other contradictions between the intersections of the four segments can be found.

As we can see from the analysis above, in some instances behavior seems to transcend category boundaries (Srivastava et al., 1984). In other cases, it does not. In cases where behavior does transcend category boundaries, the contradictions illustrated above suggest that although we may witness similar behavior across segments in different categories, these similarities may not easily be leveraged if segmentation was derived from analyzing each category individually. In the next section, we present the results from deriving the segmentation by considering the categories jointly to overcome the shortcomings mentioned above.

Finally, it is interesting to ask how sensitive the results are to the number of categories analyzed. From the model comparisons in Table 3 we see that it depends on the categories analyzed. Including purchase feedback from towels helps improve the model fit and prediction accuracy for diapers. And, including purchase feedback from diapers improves the model fit and prediction accuracy for towels. Interestingly, model fit and predictive accuracy actually decreases when purchase feedback from formula alone is included in a single-category analysis of diapers or of towels. Further, the best fitting model included purchase feedback from both non-focal categories. It is difficult to generalize the effect of number of categories considered; the effects depend on which categories are used. However, if one focuses on the best performing models for two and then three categories considered, there does appear to be a decreasing benefit to more categories.

6. Results—segmentation from analyzing categories jointly

Our shift from analyzing categories individually to analyzing categories jointly followed a step-wise process. We first began by examining models where the segmentation scheme was still derived at the individual category level, however information from other categories, specifically purchase feedback, was included in the model. The results from these models can once again be found in Table 3.

The improvement in model fit from introducing purchase feedback from a non-focal category depends on what categories are in the analysis. In the diaper category, there is a greater improvement in fit when also considering past towel purchases, than when considering past purchase of baby formula. In the towel category, the ability to predict towel purchases is greater when considering past diaper purchases, than when considering past formula purchases. In the formula category, there is virtually no difference in the improvement of fit, regardless of whether past purchases of diapers or towels are considered.

These findings provide initial insights into the relationships between these three categories, which we defined earlier as “weak” compliments. Specifically, they suggest there is a greater relationship between diaper and towel purchases than there is between formula and towel purchases or formula and diaper purchases. Therefore, if a manager of say a towel brand were faced with budget constraints or data constraint, he/she would be better off considering consumers’ diaper purchases rather than formula purchases for insights into the purchase behavior of the consumers in his/her category. Likewise, a manager of diapers would derive greater benefits from considering the same consumers’ purchases of towels rather than formula purchases. However, having said all of this, we note that in all three categories a three-segment model with purchase feedback from *both* non-focal categories performed best.

Next, we compared models where segmentation was derived from analyzing two categories at a time. Again we find that the greatest improvement in fit is obtained when considering towels and diapers jointly (BIC = 40,180.15, hit-rate = 0.539). This supports the results discussed above and could possibly be driven by the fact that common national brands exist across these two categories. The next best improvement in fit is obtained when considering towels and formula jointly (BIC = 40,687.47, hit-rate = 0.531). Synergies between diapers and formula seem to be the weakest (BIC = 41,028.47, hit-rate = 0.523). Finally, we considered models that derived segmentation when all three categories were considered jointly and purchase feedback from all three categories was considered. Here we find that a six-segment model best fits the data (BIC = 59,680.44, hit-rate = 0.570).

To further facilitate the comparison of the best fitting multiple-category models with the corresponding, best fitting individual category models, we constructed a BIC-type statistic. For l categories, we defined a BIC-type measure for the individual category models as follows:[4]

$$\mathrm{BIC} = -2 \times \left(\left(\sum_l LL_l \right) - 0.5 \times \ln \left(\sum_l n_l \right) \times \left(\sum_l k_l \right) \right) \tag{12}$$

For each individual category, we utilized the best fitting model under two different scenarios. First, where *LBP* was restricted to only the focal category and second, where *LBP* included terms for purchases made outside the focal category. Using the data from Table 3, the comparisons are summarized below:

BIC-type comparison of individual and multiple-category models

	Separate individual category models (using Eq. (12))		Multiple category model (from Table 3)
	LBP for focal category only[a]	LBP includes multiple categories[a]	LBP for focal categories only[a]
Diapers and towels	41,383.43	41,350.50	40,180.15
Diapers and formula	40,091.41	39,548,54	40,981.26
Towels and formula	41,334.36	40,816.19	40,734.68
Diapers, towels and formula	61,463.29	60,808.24	59,680.44

[a] In all cases, the best fitting model was a three-segment model, except for the joint model with all three categories.

Examining across rows, we find that the multiple category approach out-performs the single category models in all cases except for the diapers and formula pair. This model also has the lowest hit rate amongst the joint models (Table 3). Support is strongest when diapers and towels are considered jointly—the categories with common brands.

Based on the results from Table 3 and the table presented above, we can conclude that the best-fitting joint category model was the six-segment model spanning all three categories. The maximum likelihood results for this model are shown in Table 8a–c. Table 8a presents the results for Segments J1 and J2, Table 8b presents the results for Segments J3 and J4, and Table 8c presents the results for Segments J5 and J6.

Table 9a and b summarizes some of the important findings. The top portion of Table 9a and b summarizes the trends in brand preferences by reporting the "initial" value (*Age* = 1 week) of intrinsic brand preferences and the trend over time spent purchasing in the category (i.e., the trend with the log of *Age*). The bottom portion of the table reports the segment membership descriptors using posterior analysis and the available demographic data. Table 9a reports these findings for Segments J1, J2 and J3. Table 9b reports these findings for Segments J4, J5 and J6. The following discusses the results for intrinsic brand preferences, followed by a discussion of price sensitivity and sensitivity to purchase feedback.

6.1. Brand preferences

The summary results presented in Table 9a and b highlight some opportunities for brands that compete in multiple categories or that might want to leverage other categories to benefit their brands.

To begin, we find similarities in brand preferences across the three categories for consumers in Segment J2. For low values of *Age*, consumers in J2 have a strong preference for the leading national brand, and in the case of towels and formula, preferences for some of the medium and small tier brands. Over time, preferences for private label brands increase in the categories where private labels are available (diapers and towels), as do preferences for middle and small tier brands.

As highlighted above, an analysis that proceeds by combining segmentation results from categories that were analyzed separately can result in conflicting profiles based on demographic information for segments that are similar across categories in terms of their brand preference and/or responsiveness to marketing actions. The problem of conflicting profiles across categories is not an issue when the analysis uses information from the categories jointly. We identify consumers in Segment J2 as being predominantly first-time, younger moms. To take advantage of these results, a private label brand that competes in

[4] We thank a reviewer and the Editor for suggesting this.

Table 8

(a) Maximum likelihood estimates for joint three category model—segments J1 and J2

Variable	Segment J1			Segment J2		
	Diapers	Towels	Formula	Diapers	Towels	Formula
Intrinsic brand preference[a]						
Brand2	− 0.56 * (− 2.4)	− 1.42 * * (− 5.3)	–	− 0.84 * * (− 4.7)	− 0.83 * * (− 2.9)	–
Brand2 × ln(Age_t^h)	0.09 (1.2)	0.03 (0.5)	–	0.05 (0.8)	0.14 (1.5)	–
Brand3	− 1.73 * * (− 5.1)	− 2.74 * * (− 8.2)	–	− 3.19 * * (− 8.7)	− 1.70 * * (− 4.1)	–
Brand3 × ln(Age_t^h)	0.74 * * (6.8)	− 0.01 (− 01)	–	0.41 * * (4.9)	0.41 * * (3.6)	–
Brand4	− 4.22 * * (− 7.6)	–	–	− 5.58 * * (− 9.1)	–	–
Brand4 × ln(Age_t^h)	1.26 * * (7.1)	–	–	0.87 * * (8.2)	–	–
Brand5	–	− 2.16 * * (− 5.9)	–	–	− 0.54 (− 0.3)	–
Brand5 × ln(Age_t^h)	–	0.02 (0.2)	–	–	0.23 * * (2.5)	–
Brand6	–	− 1.67 * * (− 5.3)	–	–	− 0.94 * * (− 2.6)	–
Brand6 × ln(Age_t^h)	–	− 0.07 (− 0.8)	–	–	0.26 * * (2.6)	–
Brand8	–	–	− 1.75 * (− 2.4)	–	–	− 0.91 * (− 2.1)
Brand8 × ln(Age_t^h)	–	–	− 0.02 (− 0.1)	–	–	0.42 * * (2.7)
Brand9	–	–	− 0.28 (− 0.6)	–	–	− 0.23 (− 0.4)
Brand9 × ln(Age_t^h)	–	–	− 0.37 * * (− 3.0)	–	–	0.16 (1.0)
Brand10	–	–	− 0.61 * (− 2.0)	–	–	− 1.42 * (− 2.3)
Brand10 × ln(Age_t^h)	–	–	− 0.04 (− 0.4)	–	–	0.14 (0.6)
Brand11	–	–	− 0.95 (− 1.5)	–	–	− 3.72 * * (− 4.6)
Brand11 × ln(Age_t^h)	–	–	− 0.43 * (− 2.4)	–	–	0.96 * * (4.3)
Brand12	–	–	− 0.81 (− 1.5)	–	–	− 0.78 (− 1.2)
Brand12 × ln(Age_t^h)	–	–	− 0.40 * * (− 2.7)	–	–	− 0.50 * * (− 2.5)
PLabel	− 3.08 * * (− 5.2)	− 1.75 * * (− 5.6)	–	− 2.61 * * (− 7.4)	− 3.20 * * (− 5.7)	–
PLabel × ln(Age_t^h)	0.09 (1.3)	− 0.11 (− 1.3)	–	1.07 * * (9.5)	0.99 * * (6.9)	–
Other	− 2.24 * * (− 7.5)	− 1.59 * * (− 4.7)	− 0.78 (− 1.3)	− 3.46 * * (− 6.6)	− 0.01 (− 0.1)	− 1.57 * (− 2.2)
Other × ln(Age_t^h)	0.89 * * (9.7)	− 0.12 (− 1.3)	− 0.39 * (− 2.3)	0.36 * * (5.2)	0.34 * * (3.4)	0.26 (1.3)

(continued on next page)

Table 8 (*continued*)

(a) Maximum likelihood estimates for joint three category model—segments J1 and J2

Variable	Segment J1			Segment J2		
	Diapers	Towels	Formula	Diapers	Towels	Formula
Feedback						
$LBP_{it}^{h,\text{diapers}}$	2.41** (15.3)	0.11* (1.8)	−0.39 (−0.2)	1.51** (12.6)	1.10 (1.2)	0.37 (0.4)
$LBP_{it}^{h,\text{diapers}} \times \ln(Age_t^h)$	−0.09 (−1.8)	0.02* (1.7)	−0.33 (−0.5)	0.03 (0.7)	1.08 (0.5)	0.60 (0.9)
$LBP_{it}^{h,\text{towels}}$	2.16* (2.3)	1.02** (5.1)	1.22 (1.3)	1.41 (1.4)	2.19* (2.1)	1.17 (0.4)
$LBP_{it}^{h,\text{towels}} \times \ln(Age_t^h)$	0.17 (0.3)	0.33* (1.8)	−0.31 (−0.1)	0.42 (0.5)	0.97** (3.4)	0.42 (1.0)
$LBP_{it}^{h,formula}$	−0.04 (−0.3)	0.57* (1.9)	−0.28 (0.9)	1.26* (1.9)	2.03** (3.9)	2.37** (4.2)
$LBP_{it}^{h,\text{formula}} \times \ln(Age_t^h)$	0.12 (0.3)	0.23 (0.8)	0.04** (4.7)	−0.41* (−1.8)	0.03** (3.7)	0.13* (1.9)
Price						
$price_{it}$	−5.76** (−8.5)	−1.01 (−1.1)	−2.12** (−7.1)	−3.51** (−9.2)	−2.19* (−2.1)	−4.39** (−4.0)
$price_{it} \times \ln(Age_t^h)$	−0.07 (−0.1)	−0.25* (−1.8)	−0.21** (−2.5)	0.47* (1.8)	0.21** (3.4)	−0.53 (−0.3)
Segment size	0.23* (2.1)			0.19* (1.9)		
N—customers	397					
N—purchases	27,598					
Log-likelihood	−34,035.42					
BIC criterion	71,680.44					
Hit rate	0.59					

(b) Maximum likelihood estimates for joint three category model—segments J3 and J4

Variable	Segment J3			Segment J4		
	Diapers	Towels	Formula	Diapers	Towels	Formula
Intrinsic brand preference[a]						
Brand2	−1.59** (−6.5)	−1.40 (−0.4)	–	−1.39** (−8.4)	−1.19** (−3.5)	–
Brand2 × $\ln(Age_t^h)$	0.21 (0.5)	0.21 (0.4)	–	0.09 (1.5)	0.02* (2.4)	–
Brand3	−1.35** (−2.5)	−1.64* (−1.9)	–	−2.14** (−9.6)	−3.23** (−6.1)	–
Brand3 × $\ln(Age_t^h)$	−0.29 (−0.3)	−0.63 (−0.2)	–	1.76** (7.6)	0.30* (2.1)	–
Brand4	−2.34** (−4.1)	–	–	−1.74** (−5.5)	–	–
Brand4 × $\ln(Age_t^h)$	1.16 (0.8)	–	–	1.06** (8.3)	–	–
Brand5	–	1.32 (1.1)	–	–	−0.69* (−2.4)	–
Brand5 × $\ln(Age_t^h)$	–	0.41 (0.8)	–	–	−0.01 (−0.2)	–
Brand6	–	−0.14 (−1.0)	–	–	−1.43** (−4.1)	–
Brand6 × $\ln(Age_t^h)$	–	−0.26 (−0.6)	–	–	0.07 (0.6)	–
Brand8	–	–	−2.46** (−4.5)	–	–	−1.62* (−2.0)
Brand8 × $\ln(Age_t^h)$	–	–	1.00* (1.9)	–	–	0.52 (0.8)

Table 8 (*continued*)

(b) Maximum likelihood estimates for joint three category model—segments J3 and J4

Variable	Segment J3			Segment J4		
	Diapers	Towels	Formula	Diapers	Towels	Formula
Intrinsic brand preference[a]						
Brand9	–	–	−1.23** (−3.5)	–	–	0.33 (0.7)
Brand9 × $\ln(Age_t^h)$	–	–	1.40* (2.0)	–	–	−0.41* (−2.1)
Brand10	–	–	−2.35** (−3.3)	–	–	−0.49** (−2.8)
Brand10 × $\ln(Age_t^h)$	–	–	0.05 (0.1)	–	–	−0.01 (−0.1)
Brand11	–	–	−2.09** (−3.3)	–	–	−0.52 (−1.2)
Brand11 × $\ln(Age_t^h)$	–	–	0.32 (0.4)	–	–	−0.93** (−2.9)
Brand12	–	–	−1.42* (−1.8)	–	–	−0.66 (−1.2)
Brand12 × $\ln(Age_t^h)$	–	–	−0.23 (−0.4)	–	–	−0.20* (−1.8)
PLabel	−1.56** (−3.9)	0.45* (2.1)	–	−2.24** (−6.6)	−0.61* (−2.2)	–
PLabel × $\ln(Age_t^h)$	0.46* (2.1)	0.22* (2.4)	–	0.92** (2.9)	−0.03 (−0.3)	–
Other	−1.39** (−5.6)	0.25** (4.6)	−1.45* (−2.1)	−1.34** (−9.5)	−0.51 (−1.3)	−1.42 (−0.6)
Other × $\ln(Age_t^h)$	1.21** (3.5)	−1.35 (−1.3)	−0.34* (−1.9)	0.96** (7.1)	−0.10 (−1.1)	−1.02** (−4.1)
Feedback						
$LBP_{it}^{h,\text{diapers}}$	−1.60 (−1.1)	2.10** (2.9)	1.37** (3.4)	0.91** (4.5)	0.37* (2.0)	0.45** (3.8)
$LBP_{it}^{h,\text{diapers}} \times \ln(Age_t^h)$	−0.13 (−0.7)	0.92** (3.5)	0.63** (2.9)	0.21** (3.3)	0.13** (3.4)	1.33** (3.5)
$LBP_{it}^{h,\text{towels}}$	−1.41 (−1.4)	1.83* (1.9)	1.02** (4.1)	−0.41 (−1.1)	−0.02 (−0.3)	−1.18 (−0.5)
$LBP_{it}^{h,\text{towels}} \times \ln(Age_t^h)$	0.42** (2.5)	0.29 (0.3)	0.16* (1.8)	1.27 (0.3)	1.41** (6.7)	−0.62 (−0.5)
$LBP_{it}^{h,\text{formula}}$	−0.34 (−0.3)	1.05** (3.3)	0.42** (2.9)	0.12 (0.9)	1.07 (0.3)	−0.32 (−0.5)
$LBP_{it}^{h,\text{formula}} \times \ln(Age_t^h)$	0.58* (2.1)	0.67** (2.5)	0.21** (4.7)	0.66 (1.4)	0.24 (1.1)	1.27** (6.3)
Price						
$price_{it}$	−0.44* (−2.0)	−1.27* (−1.9)	−0.93** (−3.2)	−5.27** (−9.9)	−0.24** (−3.8)	1.37 (0.2)
$price_{it} \times \ln(Age_t^h)$	0.67 (0.9)	0.03* (2.1)	0.04** (6.3)	−1.07** (−7.1)	−2.16** (−9.2)	−0.07* (−2.0)
Segment size	0.16* (4.1)			0.14* (1.7)		
N—customers	397					
N—purchases	27,598					
Log-likelihood	−34,035.42					
BIC criterion	71,680.44					
Hit rate	0.59					

(continued on next page)

Table 8 (*continued*)

(c) Maximum likelihood estimates for joint three category model—segments J5 and J6

Variable	Segment J5			Segment J6		
	Diapers	Towels	Formula	Diapers	Towels	Formula
Intrinsic brand preference[a]						
Brand2	0.34 (1.5)	− 0.45 (− 0.3)	–	1.34 (0.5)	0.83 (1.0)	–
Brand2 × ln(Age_t^h)	0.22 (0.5)	1.34 (0.5)	–	0.25 * * (2.6)	0.66 (1.1)	–
Brand3	2.67 (0.5)	− 1.45 (− 1.2)	–	3.22 (1.2)	− 1.53 * (− 2.2)	–
Brand3 × ln(Age_t^h)	0.26 * (2.3)	0.22 (0.9)	–	0.86 * (2.4)	0.93 (0.3)	–
Brand4	− 1.01 * * (− 2.8)	–	–	− 0.34 (− 0.8)	–	–
Brand4 × ln(Age_t^h)	0.17 (0.5)	–	–	1.32 * (1.8)	–	–
Brand5	–	0.35 (1.2)	–	–	− 1.20 (− 0.3)	–
Brand5 × ln(Age_t^h)	–	0.28 (0.5)	–	–	− 1.43 (− 1.3)	–
Brand6	–	− 0.36 (− 1.1)	–	–	− 1.04 (− 0.9)	–
Brand6 × ln(Age_t^h)	–	− 2.76 (− 0.3)	–	–	− 1.93 (− 0.8)	–
Brand8	–	–	2.06 (1.6)	–	–	− 1.46 * * (− 4.5)
Brand8 × ln(Age_t^h)	–	–	0.40 * * (2.9)	–	–	0.35 * * (5.6)
Brand9	–	–	1.19 (0.5)	–	–	− 1.24 * * (− 3.5)
Brand9 × ln(Age_t^h)	–	–	1.82 * (2.0)	–	–	1.70 * (2.2)
Brand10	–	–	− 0.49 (− 0.3)	–	–	− 2.31 * (− 2.2)
Brand10 × ln(Age_t^h)	–	–	0.04 (0.8)	–	–	0.05 (0.1)
Brand11	–	–	− 1.28 (− 1.3)	–	–	− 1.54 * * (−2.9)
Brand11 × ln(Age_t^h)	–	–	0.05 (0.1)	–	–	0.02 (0.8)
Brand12	–	–	− 0.99 (− 1.2)			− 1.12 * * (− 6.2)
Brand12 × ln(Age_t^h)	–	–	0.13 (0.2)	–	–	− 0.04 (− 0.4)
PLabel	− 1.59 * * (− 3.5)	0.95 (0.1)	–	− 1.33 * * (− 5.1)	− 2.01 * (− 2.0)	–
PLabel × ln(Age_t^h)	0.46 (0.9)	− 0.14 * * (− 2.9)	–	0.93 * (1.9)	− 0.21 (− 1.4)	–
Other	− 1.23 * (− 1.9)	0.13 (1.4)	− 1.03 (− 1.1)	− 2.75 * * (− 4.9)	− 0.77 * * (− 2.9)	− 1.19 * (− 2.0)
Other × ln(Age_t^h)	1.21 (0.5)	− 0.23 (− 1.2)	− 1.42 (− 1.0)	1.89 * * (3.5)	− 0.02 * * (− 3.0)	− 0.08 (− 0.3)
Feedback						
$LBP_{it}^{h,\text{diapers}}$	1.51 * * (3.1)	0.43 (0.9)	0.94 (0.4)	2.43 * (1.9)	1.10 (0.9)	0.31 * (2.4)
$LBP_{it}^{h,\text{diapers}}$ × ln(Age_t^h)	0.32 * * (2.7)	0.62 (0.5)	0.63 (1.2)	0.06 * (2.2)	1.54 (1.5)	0.29 * * (2.7)
$LBP_{it}^{h,\text{towels}}$	− 1.43 (− 1.0)	1.23 * (2.0)	1.22 (0.4)	− 2.51 (− 1.4)	0.43 (1.0)	1.03 (1.4)
$LBP_{it}^{h,\text{towels}}$ × ln(Age_t^h)	− 0.88 (− 1.5)	0.55 (0.8)	0.77 (1.4)	1.42 (0.5)	1.39 (0.4)	2.35 (1.1)

Table 8 (*continued*)

(c) Maximum likelihood estimates for joint three category model—segments J5 and J6

Variable	Segment J5			Segment J6		
	Diapers	Towels	Formula	Diapers	Towels	Formula
Feedback						
$LBP_{it}^{h,\text{formula}}$	− 1.54	1.10 (0.9)	0.25 * *	0.03 *	1.45	1.32 * *
	(− 1.2)		(3.7)	(1.7)	(0.3)	(3.9)
$LBP_{it}^{h,\text{formula}} \times \ln(Age_t^h)$	0.38 *	0.02 (0.6)	1.45 * *	0.64 *	0.02	0.51 * *
	(1.9)		(4.7)	(2.1)	(0.3)	(5.2)
Price						
$price_{it}$	− 0.64 * *	− 0.27 *	− 0.43 *	− 2.34 *	− 0.66 * *	− 0.69 * *
	(− 2.8)	(− 2.3)	(− 1.8)	(− 1.9)	(− 4.6)	(− 6.8)
$price_{it} \times \ln(Age_t^h)$	0.27	0.24 (0.1)	0.01 * *	0.37 * *	0.17 *	0.41 * *
	(0.9)		(4.3)	(2.9)	(2.0)	(2.8)
Segment size	0.17* * (2.8)			0.11* * (4.0)		
N—customers	397					
N—purchases	27,598					
Log-likelihood	− 34,035.42					
BIC criterion	71,680.44					
Hit rate	0.59					

[a] Normalized on Brand 1 in the Diaper and Towel categories and on Brand 7 in the Formula category.

* Significant at 0.05.

** Significant at 0.01.

both the diaper and towel category for example, could target these younger, first-time moms early in their purchasing history with promotions for both products in an effort to build their loyalty early. Or, a big, national brand that competes in multiple categories and appears to be losing market share among the consumers in this segment may try to target these younger, first-time moms with cross-promotions for its brands in an effort to keep them over their lifetime in the category.

Consumers in J5 are brand indifferent for towels and formula, but in the diaper category they initially prefer the leading national brand and its closest competitor. Over time there is an increase in preference for middle tier brands in the diaper and formula categories. Therefore, leading national brands in the diaper category that also compete in the towel and/or are considering entering the formula category, should try to leverage their popularity among consumers in this segment (lower-class, older mothers who tend to shop at mass merchants) who currently buy their diapers in an effort to grow sales in the towel and formula categories. This would be true for say Brands 1, 2 and 3, which are the same brand across the diaper and towel category. Furthermore, if a middle-tier brand competed in all three categories, it should look for ways to leverage the growing preference for its brand in the formula and diaper categories in order to benefit in the towel category. One example would be to distribute an incentive on the package of a middle tier diaper or formula brand that was good for the same middle tier brand in the towel category. Or the same incentive could be distributed to lower-class, older moms who show an affinity for middle-tier formula and diaper brands, but seem to be brand indifferent in the towel category.

Consumers in Segment J6 behave similarly in that they are averse to private label and/or small brands early in their purchasing history in diapers and for their entire purchasing history in towels and formula. Therefore, a brand that competes in either the middle or lower quality tiers across some or all of these categories could provide incentives to these consumers to purchase their brands.

Finally, consumers in Segment J4, older moms of baby girls living in urban areas, seem to prefer leading national brands in the diaper, towel and formula categories early in their purchasing history. Preferences for diapers and towels shift to middle-tier and smaller brands over time whereas preferen-

Table 9

(a) Brand preference trends and profiles for segments J1, J2 and J3

Category	Segment J1 (23%)			Segment J2 (19%)			Segment J3 (16%)		
	Diapers	Towels	Formula	Diapers	Towels	Formula	Diapers	Towels	Formula
Initial preferences	Leading national brand	Leading national brand	Leading national brand, small, and some med.	Leading national brand	Leading national brand, some med. and small	Leading national brand, some med. and small	Leading national brand	Leading national brand, top comp. and some middle tier	Leading national brand
Trend in preferences for...									
Leading national brand									
Middle tier brand	↑↑		↓	↑↑	↑↑↑	↑			↑↑
Small brands	↑		↓↓↓	↑	↑	↑ ↓	↑		↓
Private label			NA	↑	↑	NA	↑	↑	NA
Segment descriptors									
First-time mom	0.15** (2.9)			0.13* (2.4)			− 0.21 (− 0.8)		
Working mom	− 0.11* (− 1.9)			− 0.24 (− 0.2)			0.30 (1.0)		
Upper class	0.11* (2.0)			0.11 (0.5)			− 0.38 (− 0.1)		
Mom age	0.10** (5.7)			− 0.12* (− 2.0)			− 0.19* (− 2.1)		
Mass_Merch	− 0.42 (− 0.5)			0.26 (0.8)			− 0.60* (− 2.2)		
Boy gender	0.77 (1.6)			0.14 (0.5)			0.61 (0.2)		
City domicile	− 0.24 (− 0.4)			− 0.30 (− 1.2)			0.22 (0.7)		
R^2	0.11			0.08			0.06		

(b) Profiles for segments J4, J5 and J6

Category	Segment J4 (14%)			Segment J5 (17%)			Segment J6 (11%)		
	Diapers	Towels	Formula	Diapers	Towels	Formula	Diapers	Towels	Formula
Initial preferences	Leading national brand	Leading national brand and small	Leading national brand, small, and some med.	Leading national brand and top comps.	Brand indifferent	Brand indifferent	Avoid small brands and private labels	Avoid some med., small brands and private labels	Leading national brand
Trend in preferences for...									
Leading national brand									
Middle tier brand	↑↑	↑↑	↓	↑		↑↑	↑↑↑		↑↑
Small brands	↑		↓↓↓				↑	↓	↓
Private label	↑		NA		↓	NA	↑		NA
Segment descriptors									
First-time Mom	0.20 (0.7)			− 0.16 (− 0.3)			0.29** (2.7)		

Table 9 (*continued*)

(b) Profiles for segments J4, J5 and J6

Category	Segment J4 (14%)			Segment J5 (17%)			Segment J6 (11%)		
	Diapers	Towels	Formula	Diapers	Towels	Formula	Diapers	Towels	Formula
Segment descriptors									
Working Mom	− 0.27			0.54			0.23 (1.2)		
	(− 0.8)			(1.0)					
Upper class	0.53			− 0.15**			− 0.33 *		
	(0.2)			(− 2.8)			(− 1.9)		
Mom age	0.27**			0.11**			− 0.14 *		
	(2.7)			(3.5)			(2.3)		
Mass_Merch	− 0.54			0.13 *			0.15 (0.6)		
	(− 0.1)			(2.3)					
Boy gender	− 0.37 *			− 0.20			− 0.18		
	(− 2.0)			(− 0.4)			(− 1.1)		
City Domicile	0.83 *			− 0.32			− 0.44		
	(2.3)			(− 0.5)			(− 0.2)		
R^2	0.10			0.13			0.08		

Maximum number of arrows: diaper (3 medium, 1 small, 1 private label); towel (4 medium, 1 small, 1 private label); formula (3 medium, 3 small). NA = not applicable (no private label in formula category).

* Significant at 0.05.

** Significant at 0.01.

ces for middle-tier and smaller brands diminish over time in the formula category. Therefore, smaller brands that compete in all three categories may wish to target incentives for formula at consumers in this segment who already buy their diaper or towel brand with the hopes that they would switch away from their big name formula brand to the same small brand they use in diapers or towels.

The discussion above provides some examples of how insights from considering brand preferences jointly across categories can be exploited in ways that would not be possible when considering categories individually. The following section discusses the same types of insights to be gained when looking at price sensitivity.

6.2. Price sensitivity

Table 10 shows the direct price elasticity of a brand given a decrease in price equal to one standard deviation below its mean (all other variables held constant at their means). Elasticities are calculated for consumers at the fifth purchase (i.e., early in their purchasing history) and then later in the category at the 30th purchase occasion.

The table below summarizes some of the information in Table 10. It presents the rank order for price sensitivity for each segment by category for the appropriate leading national brand. We label "initial" as the rank at the 5th purchase and "later" as the rank at the 30th purchase occasion. A ranking of "1" indicates that the segment is the *most* sensitive segment to price for the leading national brand at the given purchase occasion. A ranking of "6" indicates the segment is the *least* sensitive to price for the leading national brand. The arrows indicate the trend in price sensitivity over time within each segment. For example, consumers in J1 are the most sensitive to diaper prices of the leading national brand of all the six segments at the 5th purchase as well as at the 30th purchase. However, consumers in this segment become less sensitive to price over time as indicated by the downward arrow. On the other hand, consumers in J4 are the least sensitive of all the segments to the price of the leading national diaper brand at the fifth purchase and at the 30th purchase in the formula category. Furthermore, consumers' sensitivity to price in this segment increases over purchases, as indicated by the upward pointing arrow. Although this discussion focuses on the leading national brand only,

Table 10
Sensitivity analysis for price[a]

	Segment J1 (23%)						Segment J2 (19%)					
	Diapers		Towels		Formula		Diapers		Towels		Formula	
	Initial[b]	Trend[b]	Initial	Trend	Initial	Trend	Initial	Trend	Initial	Trend	Initial	Trend
Brand 1	0.2099	0.1056	0.0062	0.0081	–	–	0.1147	0.0598	0.0061	0.0038	–	–
Brand 2	0.1100	0.0567	0.0024	0.0033	–	–	0.0621	0.0239	0.0026	0.0017	–	–
Brand 3	0.0904	0.1342	0.0002	0.0008	–	–	0.0105	0.0069	0.0013	0.0013	–	–
Brand 4	0.0197	0.0763	–	–	–	–	0.0021	0.0033	–	–	–	–
Brand 5	–	–	0.0010	0.0014	–	–	–	–	0.0031	0.0022	–	–
Brand 6	–	–	0.0015	0.0018		–	–	–	0.0024	0.0017	–	–
Brand 7	–	–	–	–	0.0037	0.0047	–	–	–	–	0.0079	0.0079
Brand 8	–	–	–	–	0.0009	0.0012	–	–	–	–	0.0053	0.0082
Brand 9	–	–	–	–	0.0018	0.0015	–	–	–	–	0.0058	0.0064
Brand 10	–	–	–	–	0.0022	0.0029	–	–	–	–	0.0021	0.0022
Brand 11	–	–	–	–	0.0007	0.0005	–	–	–	–	0.0005	0.0018
Brand 12	–	–	–	–	0.0013	0.0010	–	–	–	–	0.0013	0.0004
PLabel	0.0091	0.0045	0.0008	0.0009	–	–	0.0458	0.0630	0.0005	0.0013	–	–
"Other"	0.0769	0.1432	0.0011	0.0012	0.0012	0.0009	0.0076	0.0051	0.0043	0.0036	0.0017	0.0002

	Segment J3 (16%)						Segment J4 (14%)					
	Diapers		Towels		Formula		Diapers		Towels		Formula	
	Initial	Trend	Initial	Trend	Initial	Trend	Initial	Trend	Initial	Trend	Initial	Trend
Brand 1	− 0.0176	− 0.0137	0.0022	0.0014	–	–	0.1199	0.0170	0.0148	0.0312	–	–
Brand 2	− 0.0072	− 0.0068	0.0005	0.0005	–	–	0.0297	0.0038	0.0049	0.0097	–	–
Brand 3	− 0.0038	− 0.0014	0.0001	0.0000	–	–	0.1754	0.3019	0.0009	0.0027	–	–
Brand 4	− 0.0124	− 0.0513	–	–	–	–	0.0980	0.0817	–	–	–	–
Brand 5	–	–	0.0039	0.0003	–	–	–	–	0.0062	0.0118	–	–
Brand 6	–	–	0.0007	0.0003	–	–	–	–	0.0036	0.0079	–	–
Brand 7	–	–	–	–	0.0010	0.0000	–	–	–	–	− 0.0017	− 0.0014
Brand 8	–	–	–	–	0.0004	0.0004	–	–	–	–	− 0.0011	− 0.0017
Brand 9	–	–	–	–	0.0013	0.0005	–	–	–	–	− 0.0013	− 0.0006
Brand 10	–	–	–	–	0.0001	0.0000	–	–	–	–	− 0.0012	− 0.0010
Brand 11	–	–	–	–	0.0003	0.0000	–	–	–	–	− 0.0002	0.0000
Brand 12	–	–	–	–	0.0001	0.0000	–	–	–	–	− 0.0007	− 0.0003
PLabel	− 0.0085	− 0.0112	0.0015	0.0012	–	–	0.0435	0.0243	0.0043	0.0081	–	–
"Other"	− 0.0216	− 0.0567	0.0001	0.0000	0.0000	0.0000	0.1117	0.0705	0.0050	0.0087	0.0000	0.0000

	Segment J5 (17%)						Segment J6 (11%)					
	Diapers		Towels		Formula		Diapers		Towels		Formula	
	Initial	Trend	Initial	Trend	Initial	Trend	Initial	Trend	Initial	Trend	Initial	Trend
Brand 1	0.0001	− 0.0006	− 0.0001	0.0000	–	–	0.0025	0.0004	0.0008	0.0001	–	–
Brand 2	0.0022	− 0.0023	− 0.0004	− 0.0008	–	–	0.0122	0.0027	0.0013	0.0002	–	–
Brand 3	0.0048	− 0.0089	− 0.0021	− 0.0001	–	–	0.0302	0.0259	0.0004	0.0001	–	–
Brand 4	0.0003	− 0.0003	–	–	–	–	0.0098	0.0142	–	–	–	–
Brand 5	–	–	− 0.0003	− 0.0003	–	–	–	–	0.0001	0.0000	–	–
Brand 6	–	–	0.0000	0.0000	–	–	–	–	0.0000	0.0000	–	–
Brand 7	–	–	–	–	0.0000	0.0000	–	–	–	–	0.0000	− 0.0002
Brand 8	–	–	–	–	0.0004	0.0001	–	–	–	–	0.0000	− 0.0001
Brand 9	–	–	–	–	0.0005	0.0000	–	–	–	–	0.0001	− 0.0002
Brand 10	–	–	–	–	0.0000	0.0000	–	–	–	–	0.0000	0.0000
Brand 11	–	–	–	–	0.0000	0.0000	–	–	–	–	0.0000	0.0000

Table 10 (*continued*)

	Segment J5 (17%)						Segment J6 (11%)					
	Diapers		Towels		Formula		Diapers		Towels		Formula	
	Initial	Trend	Initial	Trend	Initial	Trend	Initial	Trend	Initial	Trend	Initial	Trend
Brand 12	–	–	–	–	0.0000	0.0000	–	–	–	–	0.0000	0.0000
PLabel	0.0006	− 0.0005	0.0000	0.0000	–	–	0.0018	0.0011	0.0000	0.0000	–	–
"Other"	0.0018	− 0.0074	− 0.0001	0.0000	0.0000	0.0000	0.0021	0.0078	0.0002	0.0000	0.0000	0.0000

[a] Δ in probability of choosing Brand *i* given a Δ in the *price* of Brand *i* equal to 1σ below the mean, all other variables at their means.
[b] "Initial" calculated at the fifth purchase occasion in the category, "Trend" calculated at the 30th purchasing occasion in the category.

similar analyses could be conducted for middle tier brands and/or small brands in any of the categories analyzed.

Price sensitivity summary for the leading national brand

	J1		J2		J3		J4		J5		J6	
	Initial	Later	Initial	Later	Initial	Later	Initial	Later	Initial	Later	Initial	Later
Diapers[a]	1	1 ↓	3	2 ↓	6	6 ↑	2	3 ↓	5	5	4	4 ↓
Towels[a]	1	1 ↑	2	3 ↓	4	4 ↓	3	2 ↑	6	6	5	5 ↓
Formula	2	2 ↑	1	1	3	3 ↓	6	6 ↑	4	3	4	5 ↑

[a] The leading national brands in the diaper and towel categories are the same brand.

Price sensitivity does not seem to be category dependent but rather segment dependent. For example, consumers in J1 seem to be the most price sensitive of the six segments to the leading national brand in each of the respective categories. Consumers in this segment (upper-class, older, first-time moms who are not working full-time) are the most price sensitive segment for diapers and towels and the second most price sensitive segment for formula. Segment J2 also seems relatively price sensitive to the leading national brand prices based on the high rankings here. In fact, J2 is the most price sensitive segment for formula and the second most price sensitive segment for diapers and towels depending on how far along the consumers are in their purchasing life-cycle. Segments J5 and J6 in general are the least sensitive to national brand prices, as indicated by the low rankings (four, fives and sixes) for those segments. Finally, segments J3 and J4 seem somewhat mixed in their overall price sensitivity. For J3, consumers are moderately sensitive to the price of the leading national towel and formula brands; however, they are the least sensitive segment to the price of the leading national brand of diapers. Consumers in J4 on the other hand are moderately price sensitive in the diaper and towel category but the least price sensitive in the formula category. The conclusion for these segments is that price sensitivity is more category dependent rather than segment dependent, at least when compared to the other four segments (J1, J2, J5 and J6).

Looking at the trend in price sensitivity over purchasing occasions, we find similarities and differences within each segment. For Segments J1, J3, J4 and J6 consumers become more sensitive to price with experience in certain categories while in other categories they become less sensitive to price. There are, however, consistencies in J2 and J5. We find that in general, consumers in J2 become less sensitive to price over time whereas consumers in J5 have a constant sensitivity to price regardless of how long they have been purchasing.

These findings provide some useful insights for these leading national brands, especially in the towel and diaper categories where the leading national brand is the same across the two categories. First, because consumers in J1 (upper-class, older, first-time moms who are not working full-time) seem to be the most sensitive to the price of the leading national brand, this would be an attractive segment for such brands to use price promotions to increase sales. For the towel and formula brands, this would be more effective when aimed at consumers in this segment later in their purchasing life-cycle, for diapers this would be most effective when aimed at consumers in this segment when first purchasing in the category. Given the leading national brand is the same brand for diapers and towels, this could present an opportunity for some types of cross-promotions. One example might be to bundle these two products at a discounted price and direct the incentive at these consumers to take advantage of their relatively high sensitivity to price in both categories. Price promotions would not seem advantageous when aimed at consumers in segments J5 and J6.

Finally, the differences across categories in J3 and J4 could lead to interesting marketing opportunities. For example, consumers in J3 seem more sensitive to the prices of the leading national brand in the towel category than they are to the leading national diaper brand, which in this case is the same brand. Therefore, the manager of this brand could target coupons for towels at consumers in this segment (younger moms who are less likely to shop at mass merchants) when they purchase the same brand of diapers.

6.3. Purchasing feedback

To analyze the sensitivity to purchase feedback, we took a case example from the diaper and towel categories to illustrate the usefulness of the results for these variables. Table 11a looks at the choice sensitivity for the leading national diaper brand (Brand 1) under different scenarios of purchase feedback (*LBP*) in both the focal (diaper) category and the non-focal (towels and formula) categories. Table 11b looks at the choice sensitivity for the leading national towel brand (Brand 1) under different scenarios of purchase feedback (*LBP*) in both the focal (towel) category and the non-focal (diaper and formula) categories. The cases presented in each table look at different combinations of purchase feedback involving the leading national brand (Brand 1) and the second leading national brand (Brand 2) in the towel and diaper categories, while assuming in all cases the leading national formula brand (Brand 7) was the last brand purchased in that category.

We present these sensitivities for when the consumer is relatively new to the category (after five purchasing occasions) and after some category experience has been accumulated (after 30 purchases). While we present these tables as an example of one possible way a sensitivity analysis for *LBP* could be conducted when segmentation is considered jointly across categories, similar analyses could be done for any other brand in any category.

Some interesting conclusions can be drawn from these results for managers of brands that compete in multiple categories (in this case Brands 1 and 2 in the towel and diaper categories). For example, if we look at cases 1 and 2 in Table 11a we see that the probability of choosing the leading national diaper brand (Brand 1) for consumers in Segments J1 and J2 is very sensitive to whether the same brand was last chosen in the towel category. Specifically, if Brand 1 was the last brand purchased (*LBP*) for both towels and diapers, and assuming the leading national formula brand was also bought, then the probability of choosing diaper Brand 1 on the fifth purchasing occasion is 0.9843 for consumers in Segment J1 and 0.9838 for consumers in Segment J2. However, if the *LBP* for towels was Brand 2, then the probability of choosing the leading national diaper brand drops to 0.5539 and 0.6490 for consumers in Segments J1 and J2, respectively. The results are even more dramatic for consumers later in their purchasing history (at purchase occasion 30—see cases 3 and 4). Interestingly, these results are not symmetric for the towel category. If we look at Table 11b, we see that the probability of choosing Brand 1 in towels for consumers in Segments J1 and J2 on the fifth purchase is 0.9377 and 0.9993, respectively, when Brand 1 was the last diaper and towel brand purchased (see cases 1 and 2). However, the change in these probabilities is not nearly as sensitive to the *LBP* in the non-focal category (diapers) here as they were above. In fact, when the second leading national brand is the *LBP* in the diaper category (case 2), we see the probabilities of choosing Brand 1 in towels only drops to 0.9261 and 0.9630 for consumers in Segments J1 and J2, respectfully. The results are similar at the 30th purchasing occasion (cases 3 and 4). These combined results suggest that just because a consumer in Segments J1 or J2 chooses diaper Brand 1 on the last purchase, the likelihood of a repeat purchase of that brand is greatly enhanced only if the same towel brand was also bought on the last purchasing occa-

Table 11

(a) Sensitivity analysis for the diaper category: the probability of choosing the leading national diaper brand (brand 1) given different purchase feedback conditions for diapers and towels[a]

Case	Purchase occasion	Last brand purchased			Segment J1	Segment J2	Segment J3	Segment J4	Segment J5	Segment J6
		LBP diaper	LBP towel	LBP formula						
1	5	Brand 1	Brand 1	Brand 7	0.9843	0.9838	0.0425	0.9093	0.0064	0.1960
2	5	Brand 1	Brand 2	Brand 7	0.5539	0.6490	0.0883	0.6179	0.1065	0.2356
3	30	Brand 1	Brand 1	Brand 7	0.9624	0.9484	0.0315	0.9723	0.0022	0.6827
4	30	Brand 1	Brand 2	Brand 7	0.3891	0.2539	0.0310	0.3653	0.1622	0.1568
5	5	Brand 2	Brand 1	Brand 7	0.6285	0.8290	0.2263	0.7187	0.0006	0.0124
6	5	Brand 2	Brand 2	Brand 7	0.0153	0.0842	0.3806	0.2324	0.0150	0.0167
7	30	Brand 2	Brand 1	Brand 7	0.6348	0.7043	0.2034	0.8715	0.0001	0.1145
8	30	Brand 2	Brand 2	Brand 7	0.0134	0.0171	0.2004	0.0607	0.0141	0.0049

(b) Sensitivity analysis for the towel category: the probability of choosing the leading national towel brand (brand 1) given different purchase feedback conditions for towels and diapers[a]

Case	Purchase occasion	Last brand purchased			Segment J1	Segment J2	Segment J3	Segment J4	Segment J5	Segment J6
		LBP towel	LBP diaper	LBP formula						
1	5	Brand 1	Brand 1	Brand 7	0.9377	0.9993	0.9965	0.9707	0.9075	0.9964
2	5	Brand 1	Brand 2	Brand 7	0.9261	0.9630	0.7861	0.9435	0.4753	0.2094
3	30	Brand 1	Brand 1	Brand 7	0.9784	0.9999	0.9998	0.9988	0.9310	0.9999
4	30	Brand 1	Brand 2	Brand 7	0.9728	0.9576	0.0850	0.9967	0.0843	0.0608
5	5	Brand 2	Brand 1	Brand 7	0.6122	0.8348	0.9564	0.6114	0.2020	0.6189
6	5	Brand 2	Brand 2	Brand 7	0.5550	0.0195	0.0591	0.3730	0.0156	0.0013
7	30	Brand 2	Brand 1	Brand 7	0.6155	0.8490	0.9948	0.2671	0.0292	0.4066
8	30	Brand 2	Brand 2	Brand 7	0.5371	0.0004	0.0172	0.0686	0.0002	0.0001

[a] Prices held at their mean value.

sion. On the other hand, the fact that the same consumer bought the leading national *towel* brand on the last purchasing ensures with great certainty that he/she will buy the same towel brand on the next occasion, regardless of whether the leading national diaper brand was last chosen. From the perspective of the manager of Brand 1 this suggests that if a consumer is already choosing Brand 1 diapers, it is very important to get that consumer to also purchase the leading national towel brand in order to maintain his/her loyalty in the diaper category. However, as long as the same consumer is purchasing the leading national towel brand, the diaper brand that he/she buys is not as crucial in maintaining loyalties to the towel brand. Once again, these types of insights are only possible when the segmentation schema is derived jointly across multiple categories.

Other observations include, for example, that for consumers in Segment J2, the choice of whether to purchase the leading national towel or diaper brand is very sensitive to whether *either* of those brands was last purchased in diapers or towels (cases 6 and 8 in both tables). If either Brand 1 in towels *or* diapers was chosen on the last purchasing occasion, then the likelihood of choosing Brand 1 in towels or diapers is relatively high. However, we see that when *neither* brand was last chosen (cases 6 and 8), there is a large decrease in the likelihood of choosing the leading national brands. In fact, we see that in almost all cases, the greatest drop in the probability of choosing either the leading national diaper or towel brand is when choice on the last purchasing occasion was for the second largest brand in *both* categories. The only exception is for consumers in Segment J3. Here we see that the probability of choosing the leading national diaper brand is actually greatest when neither the leading national diaper nor towel brands were last chosen. This would suggest a situation where consumers seek variety.

To gain some insight into the economic benefits of our joint category segmentation approach, we took the position of Brand 1, the leading brand in both the diaper and towel categories, and examined the impact of a hypothetical promotion on the joint purchase of diapers and towels targeted at price conscious buyers. First, we used the results from examining the categories separately. Consumers in segments D2 and T1 were the most price-sensitive in their respective categories, however recall from Table 5 that there were no common descriptors across these two segments (in the available data). Given the lack of overlap, the manager of the towel brand might suggest that the promotion simply be targeted at consumers in T1, selecting say residents of lower-class neighborhoods who shop primarily at mass merchants as the target. This target overlaps only with D1, customers who are less price-sensitive than D2. Assuming that only consumers in the overlap (receive and) potentially take action as a result of the joint diaper–towel promotion, that all other brands are priced at their mean, that the promotion is US$2 off the regular (operationalized as the mean) US$19 price[5] when purchasing both Brand 1 diapers and Brand 1 towels, and that the purchase is made when the baby is a newborn (3 weeks old), we calculated the change in purchase probability as a result of the promotion and the resulting economic effect. For exposition, we assumed that the probability of purchasing the brand "bundle" was the product of the purchase probabilities for the brand in each category, and that consumers "mentally" allocate the discount across the two categories in a manner that maximizes their purchase probability. Assuming a total market of 100 k buyers, the net economic effect[6] is − US$2.5 k; a loss, as the effect from the price cut is not countered by the increased volume. If the joint promotion was instead targeted to consumers in D2 (the segment likely favored by the diapers brand manager), then the target would likely be younger, first-time moms. This target overlaps only with T2, customers who are less price-sensitive than T1. Assuming as above that only consumers in the overlap (receive and) potentially take action, the net economic effect is − US$1.2 k.

Now we examine the same joint promotion implemented using the results from the joint segmentation schema. A logical target is consumers in segment J1—those who are overall the most price sensitive to towels and diapers. Under the same conditions and assumptions as above, the net economic effect is US$4.0 k. The improvement is due to the fact that consumers in the joint category segment are price sensitive to both diapers and towels. Furthermore, because this segment was estimated jointly, the demographics defining the segment are more easily identifiable. In summary, the advantage of our model is that it derives segmentation, and therefore describes consumers' behavior, across multiple categories. As we have shown in the example above, this can assist managers in developing more targeted marketing campaigns that transcend category boundaries, leading to an increase in the profitability of a promotion.

7. Discussion

We have examined insights from segmentation derived from considering consumer behavior in multiple categories jointly versus separately. We extended a traditional single-category logit-mixture model of brand choice to a multiple-category context. We add to the growing literature that empirically investigates similarities and differences across multiple product categories (e.g., Ainslie & Rossi, 1998; Chintagunta & Halder, 1998; Kim, Srinivasan, & Wilcox, 1999; Seetharaman et al., 1999).

We examined consumers purchasing in three baby-products categories, disposable diapers, towels and formula. Two of the categories, diapers and towels, have common national brands allowing us to compare results where common brands exist in multiple categories with results where this is not the case. Our results show that it is difficult to use the results of a series of single-category segmentation analyses when devising consistent and actionable strategies across all the categories in which a brand competes. For example, we found in single-category

[5] We assumed a package size of 50 diapers and 100 towels. Hence, the Brand 1 regular price for this bundle is (50 × US$0.300)+(100 × US$.040) = US$19.00.

[6] [(Discounted price) × (Purchase probability at discounted price) − (Regular price) × (Purchase probability at regular price)] × (Segment size).

analyses that older moms have a strong preference for the leading national brand in towels and in formula regardless of their baby's age. However, at the same time, while we found that there are a group of consumers who are highly price sensitive in both categories, we could not find a unique descriptor in the available demographic data to assist in targeting these customers. These results highlight the difficulty a manager of a brand competing in both categories would have using a series of single-category analyses to identify a segment of consumers that would respond to a unified marketing strategy for its brand across both product categories. Our results also support earlier findings that suggested cross-category dependency exists when consumers use the different categories as inputs in some type of consumption process or goal (Manchanda et al., 1999; Russell et al., 1999), in this case, the care of their child.

We proposed an approach to devising segments across multiple categories jointly. The results from this approach are superior to those obtained from a series of single-category analyses in that they provide a clearer understanding of the interdependencies in shopping behavior across multiple product categories. A given segment is defined by its brand preferences and response to marketing activity in multiple categories jointly, making it easier to devise cross-category programs aimed at any given customer.

Our study is not without limitations. We had access to data on the purchasing behavior of a panel of households in three product categories. Hence, our measures of cross-category purchase feedback are partial measures if some of the brands compete in categories other than those examined in this research. Hence, future research could examine more than three categories. Additional categories would also allow further investigation into the stability of the results as the number of categories increases. In addition, because we study categories where the products are somewhat related (i.e., baby products) and are typically stocked together in the store, and because previous findings on cross-category dependencies have been mixed depending on the relationship between the products studied (Manchanda et al., 1999; Russell et al., 1999; Russell & Petersen, 2000), it would be interesting to replicate this study with other categories where the products had different types of relationships, such as compliments or substitutes that were or were not stocked in close proximity to each other.

Available data precluded accounting for the effects of marketing mix variables other than price. Though discussion with the data provider indicated that variables such as advertising and coupons have limited importance in these categories (in this geographic market) their effect is well documented in the marketing literature as having an impact in other categories. Therefore, future research could seek to include the effect of other marketing instruments. The goal would be to see whether the response to each transcends multiple categories, or whether the impact is category specific.

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