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Identifying segments with identical choice behaviors across product categories: An Intercategory Logit Mixture model

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Abstract

Because consumers are limited information processors seeking to conserve cognitive energy, it is likely that at least some use identical decision heuristics across product categories. This study develops a finite mixture logit model that identifies segments of households with identical behaviors across product categories. The proposed model is shown to fit in-sample choices and forecast out-of-sample choices at least as well as an unrestricted model in which all choice behaviors are independent across product categories. The results show that about 32% of the sample households have choice behaviors that are identical across at least two of the three product categories studied, while the remaining households have choice behaviors that are independent across all three categories. The empirical results show that the segment with identical behaviors is quite price sensitive, not at all sensitive to store feature advertising, and not very brand- or size-loyal. These households are more likely to have larger families and marginally lower incomes and to shop less frequently and spend less per shopping trip. They are also lighter users in two of the three product categories investigated. Implications of the model for manufacturers and retailers are discussed. © 2002 Published by Elsevier Science B.V.

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For nearly two decades, almost all household brand choice modeling studies based on supermarket scanner data have estimated models using data from a single product category at a time. The benefits are clear. The model parameter estimates can lead to product category diagnostics that are useful for a brand manager, such as households' intrinsic preferences for various brands, price and promotion effects, loyalty effects, choice set formation, and heterogeneity in such effects across customer segments. Product category models can also be employed to derive predictions about how probabilities of choice or market shares of brands in the product category might vary depending on prices and promotions, for specific customer segments. Brand managers find diagnostic and predictive value in product category analysis.

In contrast, marketing scientists and consumer behavior scholars also have an interest in understanding effects that generalize across product categories (e.g., Bass & Wind, 1995). Because consumers are limited information processors (Bettman, 1981, p. 344; Newell & Simon, 1972) who seek to conserve cognitive energy when making perhaps dozens of purchases in lower involvement supermarket shopping environ-

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ments, they may attempt to use the same decision heuristics across product categories. For example, some households might track feature advertisements closely, and therefore show feature ad sensitivity in many product categories. Likewise, a low-income household with a large family may be very price sensitive, responding to price changes in many different product categories. Consequently, though there may be cross-sectional heterogeneity in households' responses to the marketing mix, some households may respond in the same way to the marketing mix across product categories.[1]

A general finding in the scanner data based literature is that loyalty is prevalent in low priced, frequently purchased product categories (e.g., Guadagni & Little, 1983). This finding is consistent with Howard and Sheth's (1969) theory of routinized response behavior that suggests households exhibit inertia in their brand choices over time. Using psychological theories, some researchers argue that households differ in their tendencies to exhibit loyalty because they have different optimal stimulation levels and that loyalty is a household trait (Faison, 1977; Rogers, 1979; Venkatesan, 1973).[2] If loyalty is a household trait, we would expect to see consistency across product categories in the way a household's past choices affect their current choice. In addition, if households differ in their optimal stimulation levels, it becomes important to allow for different segments when investigating consistency in loyalty effects across product categories.

The goal of this study is to identify segments of households whose choice behaviors are identical across product categories. To accomplish this goal, we develop a mixture model formulation that can be applied to multiple product categories simultaneously. Mixture models have found widespread application in marketing because of their ability to simultaneously segment a market and estimate segment level parameters. Indeed, Wedel and Kamakura (2000) cite no fewer than 40 applications in marketing, not including recent applications by Abramson, Buchmueller, and Currim (1998), Andrews and Manrai (1999), Bucklin, Gupta, and Siddarth (1998), Chintagunta and Honore (1996), Fader and Hardie (1996), and Roy, Chintagunta, and Haldar (1996). By means of posterior segment probabilities, the mixture approach provides a natural mechanism for segmenting households. For example, the model can be used to identify segments whose behaviors are identical across all three product categories studied, identical across any two of the three categories studied, or independent across all three of the categories. The existence, sizes, behaviors, and characteristics of segments whose behaviors are identical vs. independent across categories are empirical questions and are the major focus of this study.

Our study is based on purchases made in three independent product categories (liquid laundry detergent, paper towels, and margarine) by a sample of Information Resources Inc. (IRI) panelists. Using this data, we fit Intercategory Logit Mixture (ICLM) models allowing for heterogeneity in brand and size preferences, price and promotion effects, and brand and size loyalties. Fig. 1 compares the proposed ICLM modeling approach with the traditional practice of estimating independent Product Class (PC) models. With the PC model approach, an independent model is fitted to all households' purchases (in this example, 200 households' purchases) in each product class. Though the PC models may be heterogeneous and therefore segment households, the segmentation in one product category is independent of the segmentation in the other categories. The ICLM approach seeks to find homogeneous segments of households whose behaviors are identical across product categories. For example, in Fig. 1, intercategory segment 1 has identical responses to price and promotion and loyalties to brand and size effects across product categories. Intercategory segment 2, which has parameters different from those of the first, also uses identical decision

[1] Price and promotional responses can appear to be different across product categories (e.g., Narasimhan, Nelsin, & Sen, 1996) even if there are segments of consumers using identical decision heuristics across product categories. For example, if the number of purchases made by the identified segments varies across categories, price or promotion response would appear to be different across product categories even if segments display identical sensitivities to the marketing mix across product categories. Details are provided in Results.

[2] Others argue that loyalty is actually a function of the difference between the optimal and the actual level of stimulation (Steenkamp, Baumgartner, & van der Wulp, 1996; Wahlers & Etzel, 1985). Consequently, loyalty behavior of a given household will vary across categories if the categories differ in the actual levels of stimulation for the household (Hoyer & Ridgway, 1984; Steenkamp & Baumgartner, 1992; van Trijp, Hoyer, & Inman, 1996).

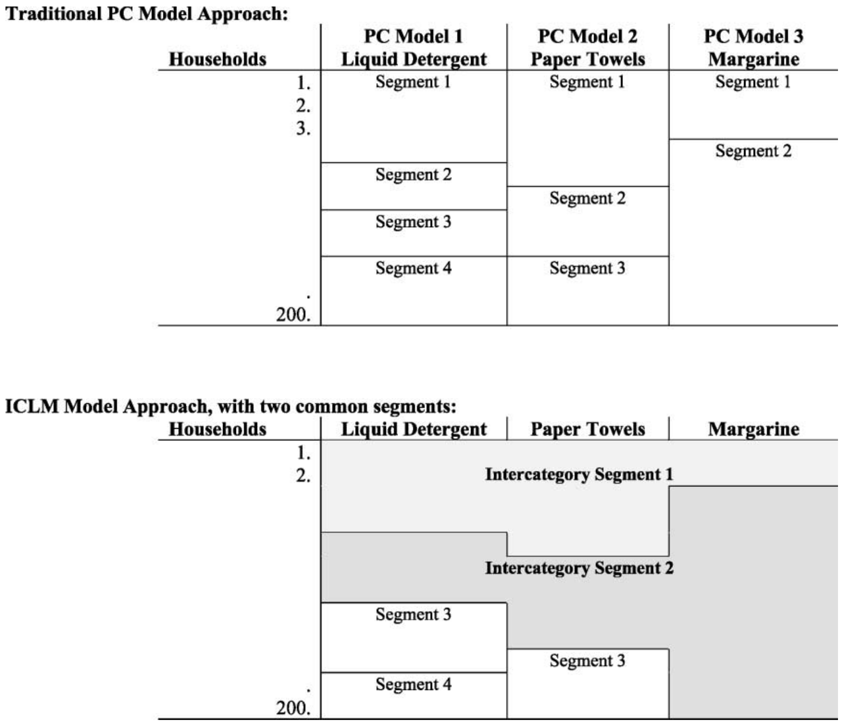

Fig. 1. Comparison of proposed Intercategory Logit Mixture (ICLM) model approach with traditional Product Class (PC) model approach.

heuristics across product categories. Other households may belong to segments with behaviors that are independent across product categories. The composition, number, size, and behavior of segments are empirically determined. Within a segment, the brand- and size-specific constants are necessarily different across product categories, and error variances may differ across product categories, but the effects of price, promotion, and loyalties are constrained to be identical across product categories.[3]

Identification of segments of households with identical behaviors across product categories could be directly useful for strategic purposes at the retailer, manufacturer, and promotion agent levels. If retailers and manufacturers can identify segments of households who respond in the same way to marketing mix strategies regardless of the product category, they may be able to improve their coordination of product assortment, pricing, and promotional strategies across categories (Russell & Kamakura, 1997). For example, a manufacturer of laundry detergents and fabric softeners may be able to offer a smaller than usual discount in one of the categories, along with a tear-off coupon for the manufacturer's brand in the other category, to entice a segment of price and promotion sensitive households to purchase products in both categories instead of just one. Likewise, Carol Wright, a promotion agent, wants to know coupon or promotion sensitivity across product categories when sending a mass-mailing of coupons. Software agents (e.g., Firefly) that perform collaborative filtering (e.g., Maes, Guttman, & Moukas, 1999) also seek to match people with similar interests across product categories.

We begin by discussing the specific research questions and previous research on this topic.

[3] Though the consumer's choice problem (e.g., number of alternatives, brands, sizes, relative prices, promotion frequencies, etc.) varies across categories, and the marketing mix parameters are constrained to be the same across categories only up to a scale factor, the *relative* sizes of coefficients are constrained to be identical across categories.

1. Research questions and background

Our major research questions are as follows:

RQ1. Are there segments of households whose choice behaviors are identical across product categories?

RQ2. If so, what are the relative sizes of segments whose behaviors are identical across categories vs. independent across categories?

RQ3. Also, how do segments of households with behaviors identical across categories differ from seg ments with behaviors independent across categories? Are their demographic characteristics different? Do their shopping behaviors differ?

These three research questions have not been addressed by the literature that studies consistency in household choice behavior across independent product categories (e.g., Ainslie & Rossi, 1998; Bawa & Shoemaker, 1987; Blattberg, Peacock, & Sen, 1976; Cunningham, 1956; Kim, Srinivasan, & Wilcox, 1999; Massy, Frank, & Lodahl, 1968; Russell & Kamakura, 1997; Seetharaman, Ainslie, & Chintagunta, 1999; Telser, 1962; Wind & Frank, 1969). We discuss the findings of these studies in the paragraphs that follow.

Early works that correlated household brand loyalty across product categories (Cunningham, 1956; Massy et al., 1968; Wind & Frank, 1969) suggest that loyalty proneness across product categories does not exist to a significant extent. Likewise, Telser (1962) found sizeable differences in price sensitivities across categories. While some greater consistency was found when investigating buying strategies (Blattberg, Peacock, & Sen, 1976), the absolute level of consistent behavior across product classes was low, even when only two product classes were compared at a time. While there is stronger evidence of coupon proneness across product categories (Bawa & Shoemaker, 1987), the strength of such proneness was much lower in one category than another.

These earlier works provide important insights. However, the analyses are not model-based and did not correct for brand and size preferences, marketing mix (price and promotion) effects, and loyalty (brand and size loyalty) as is common in studies that employ statistical models. Because of omitted variable bias, if a study finds coupon proneness or lower brand loyalty across product categories without correcting for brand preferences or accounting for marketing mix effects, it is possible that the results on the extent of coupon proneness or loyalty are downward biased.

Ainslie and Rossi (1998), Kim, et al. (1999), and Seetharaman, Ainslie, and Chintagunta (1999) develop pioneering model-based works in the area of intercategory choice. Kim et al. investigate correlation in household-level price sensitivity parameters across product categories. Bayesian analysis is applied to product categories independently to estimate the household-level price sensitivities. The correlations of price sensitivity parameters across categories are small, ranging from 0.05 to 0.18, indicating that price sensitivity may not be a fundamental household property that exists across product categories. Household demographic patterns were found to affect overall price sensitivity only to the extent that they affect shopping patterns. Demographics did not add anything to the predictive validity of the model beyond their influence on shopping patterns.

Ainslie and Rossi (1998) attribute the low intercategory price sensitivity correlations found by studies such as Kim et al. (1999) to limitations in the methodology, at least in part. They suggest that if a brand choice model is estimated for each of the available categories independently, ignoring the data in the other categories, correlations of household-level parameter estimates (e.g., corresponding to price, display, and feature sensitivity) across categories could be downward biased due to the independent sampling errors present in each parameter estimate. They avoid these biases by employing a Bayesian error components approach that introduces an explicit correlation structure across categories and provides a framework for the introduction of demographic, shopping behavior, and category-specific household variables. Their probit model utilizes the data in multiple categories simultaneously. Using data on five categories, they find correlations between parameters across categories of 0.28 for price sensitivity, 0.35 for display sensitivity, and 0.56 for feature sensitivity, indicating that these sensitivities are, to differing degrees, household traits common across categories. These correlations are much larger than the correlations obtained prior to this work. Household demographic variables are found to be more strongly related to price sensitivity than in previous studies. Higher income households are found to be less price sensitive, and larger families and households that visit the store more often are more price sensitive. Heavy user households and those with larger market baskets are found to be less price sensitive. There is only weak evidence that demographic and shopping behavior variables are important in explaining variations in display and feature sensitivity.

Seetharaman et al. (1999) extend the model proposed by Ainslie and Rossi (1998) to study the correlation of brand loyalty across product categories. They find that the loyalty parameter has an average correlation of 0.46 across product categories, indicating that households that are relatively more loyal than average in one product category are also relatively more loyal in other product categories. The inter-category correlations for price, display, and feature are 0.15, 0.24, and 0.52 (compared to the values of 0.28, 0.35, and 0.56 found by Ainslie and Rossi (1998)).

Our study builds on the contributions of these pioneering works by addressing the problem of segmentation in the context of intercategory choice. Our goal is to answer the research questions identified above: (i) Are there segments of households whose behaviors are identical across product categories? (ii) If so, what are the relative sizes of segments whose behaviors are identical across categories vs. independent across categories? (iii) In addition, how do segments with behaviors identical across categories differ from segments with behaviors independent across categories? To address these research questions, we use finite mixture models since they are particularly well-suited to segmentation problems. In contrast to the Bayesian models described above, which identify the correlations in households' responses to the marketing mix across product categories, the current study attempts to identify segments of households with identical responses to the marketing mix across two or more product categories. Since there is evidence that choice models assuming either continuous distributions of heterogeneity (estimated with hierarchical Bayesian procedures) or discrete distributions of heterogeneity (finite mixture logit choice models) are equally accurate at recovering consumer heterogeneity *even when there is within-segment heterogeneity* (Andrews, Ainslie, & Currim, 2002), the usage of finite mixture logit models is preferred given the objectives of our study.

Russell and Kamakura (1997) use a finite mixture model and long-run shopping basket data from four paper goods product categories to segment households with respect to brand name preferences. They found that preferences for retailer brand names exhibit strong consistency across product categories, but this is not so for national brand names. That study focused on consistency in household responses to brand names across product categories but did not address consistency in responses to marketing mix variables across product categories, which is the focus of the current study.

The model is described in the next section. Then we describe the results and implications of the results for marketing scientists and practitioners.

2. Model development

For the intercategory logit model estimated in this study, the basic utility specification for brand-size k at purchase occasion t (household and product category subscripts are suppressed for now) is

$$U_t^k = \alpha_i + \delta_j + x_t{}^k \cdot \beta + \mathrm{BL}_t^i \cdot \beta_{\mathrm{BL}} + \mathrm{SL}_t^j \cdot \beta_{\mathrm{SL}}, \quad (1)$$

where: α_i = the effect of brand i (i = 1, ..., I), given brand-size k has brand name i; δ_j = the effect of size j (j = 1, ..., J), given brand-size k has size j; $x_t{}^k$ = a vector of marketing mix variables, including price, store feature ad, and aisle display; β = a vector of market response parameters; BL_t^i = brand loyalty of brand i at occasion t, defined as

$$\mathrm{BL}_t^i = \lambda_{\mathrm{B}}\mathrm{BL}_{t-1}^i + (1-\lambda_{\mathrm{B}}) \cdot \begin{cases} 1 \text{ if brand } i \text{ was purchased at } t-1; \\ 0 \text{ otherwise;} \end{cases}$$

λ_{B} = the brand loyalty smoothing parameter; β_{BL} = the brand loyalty coefficient; SL_t^j = size loyalty of size j at occasion t, defined as

$$\mathrm{SL}_t^j = \lambda_{\mathrm{S}}\mathrm{SL}_{t-1}^j + (1-\lambda_{\mathrm{S}}) \cdot \begin{cases} 1 \text{ if size } j \text{ was purchased at } t-1; \\ 0 \text{ otherwise;} \end{cases}$$

λ_{S} = the size loyalty smoothing parameter; β_{SL} = the size loyalty coefficient.

The brand and size loyalty variables are based on the Guadagni and Little (1983) specification.

The choice probability for alternative k at occasion t would be formed by

$$P_t(k) = \frac{\exp(U_t^k)}{\sum_{m=1}^{K} \exp(U_t^m)}, \quad (2)$$

where K is the number of brand-size alternatives. Given Eq. (2), the probability of observing household h's choice at purchase occasion t is

$$P_{ht} = \sum_k Y_{ht}(k) \cdot P_{ht}(k), \quad (3)$$

where $Y_{ht}(k) = 1$ if household h purchased brand-size k at purchase occasion t, and 0 otherwise, and household subscripts have been added to $P_t(k)$ in Eq. (2). The probability or likelihood of observing household h's entire purchase history of T_h purchases in some product category is

$$L_h = \prod_{t=1}^{T_h} P_{ht}. \quad (4)$$

To allow heterogeneity in preferences for brands and sizes, responses to marketing mix, and brand and size loyalty, we use a mixture formulation made popular in marketing by Kamakura and Russell (1989). The mixture approach assumes that there are latent classes or segments of households whose behaviors are described by different sets of parameters. Each segment s would have its own α_i, δ_j, β, β_{BL}, and β_{SL}.[4] Since segment membership is unobservable, the overall likelihood of household h's behavior is

$$L_h = \sum_{s=1}^{S} f_s \cdot L_{h|s} \quad (5)$$

where f_s is the a priori probability that household h belongs to segment s and $L_{h|s}$ is the likelihood of observing household h's purchase history given membership in segment s, found using Eqs. (2)–(4). The expression in Eq. (4) is computed separately for each segment s, based on segment s's set of unique parameters, and the resulting likelihoods are mixed according to Eq. (5). If there are S segments, only $S-1$ parameters are required for the segment weights since $\Sigma_s f_s = 1$.

Now assume that the household makes choices in C product categories. If there are S_r latent segments in product category r, the likelihood of observing the household's history of choices in all C product categories is

$$L_h = \sum_{s_1=1}^{S_1} \sum_{s_2=1}^{S_2} \cdots \sum_{s_C=1}^{S_C} \left(f_{s_1}^{C_1} L_{h|s_1}^{C_1}\right)\left(f_{s_2}^{C_2} L_{h|s_2}^{C_2}\right) \cdots \left(f_{s_C}^{C_C} L_{h|s_C}^{C_C}\right), \quad (6)$$

where the $f_{S_r}^{C_r}$ are the prior probabilities of segment membership for product category r,

$$\sum_{s_1=1}^{S_1} f_{s_1}^{C_1} = \sum_{s_2=1}^{S_2} f_{s_2}^{C_2} = \cdots = \sum_{s_C=1}^{S_C} f_{s_C}^{C_C} = 1.$$

Note that Eq. (6) reduces to a traditional finite mixture logit model when there is only one product category. In a two product category example in which behaviors in both categories are well-described by two latent segments, the overall likelihood for household h in Eq. (6) would involve the summation of four terms, corresponding to the household belonging to: segment 1 for both categories, segment 1 for category 1 and segment 2 for category 2, segment 2 for category 1 and segment 1 for category 2, and segment 2 for both categories.

The brand (α_i) and size (δ_j) constants necessarily vary across product classes (e.g., there is Tide detergent but no Tide paper towels). For each segment in which behaviors are constrained to be identical across categories, the vector of responses to marketing variables (β) and the brand and size loyalty coefficients (β_{BL}, β_{SL}) are the same across product categories, up to a constant scale factor (Swait & Louviere, 1993). For example, if β is the vector of responses to marketing mix and loyalty for some segment for the liquid detergent category, then the vector of responses

[4] The smoothing parameters λ_B and λ_S are estimated using a homogeneous logit model and then held constant across segments in the heterogeneous models to reduce the complexity of the estimation and to enhance the stability of the model. We did estimate some models that allowed the smoothing parameter values to vary across segments. We found that removing this nonlinearity from the estimation reduced estimation time by 75–80%. In addition, the effect on fit was negligible. Likelihood functions are typically very flat with respect to the smoothing parameters.

for this segment for the paper towel category is $\mu_1\beta$, where μ_1 is the estimated scale factor for this segment for the paper towel category. Likewise, the vector of responses for this segment for the margarine category is $\mu_2\beta$, where μ_2 is the scale factor for this segment for the margarine category. Swait and Louviere (1993) show that it is possible to identify the relative scale factor in two or more data sets. For example, if we fix the scale factor of one product category (say liquid detergent) to the commonly accepted value of 1.0, then we may empirically estimate the scale factors for the other product categories (margarine and paper towels), assuming common β. This allows for choice error variance ($\sigma_\varepsilon{}^2$), which is induced by factors that remain unobservable to the researcher (e.g., situational factors), to vary across product categories. However, the underlying choice behavior described by β remains identical across categories.

We also allow for behaviors that are not identical across product categories. For example, if three product categories have two, three, and four latent segments, respectively, we can impose the common parameters restrictions for all categories on one or at most two segments.[5] The product categories with more than two segments would have other segments whose behaviors are not shared in other categories. We can use model selection criteria to determine whether there should be one or two segments with common parameter restrictions across all product categories.

The overall log likelihood function maximized to estimate the parameters is

$$L = \sum_h \ln(L_h). \tag{7}$$

As is customary, the number of segments needed to characterize household preferences in each product category is determined empirically, using such criteria as BIC. For simplicity, we determine the number of segments required in each product category using independent product class models before estimating the intercategory logit mixture model.[6]

To allocate households to segments, posterior segment probabilities can be used. For example, if segment r is constrained to have common parameters across product categories, the likelihood that household h belongs to common segment r in all C product categories is

$$\pi^h_{rr\ldots r} = \frac{(f_r^{C_1} L_{h|r}^{C_1})(f_r^{C_2} L_{h|r}^{C_2})\cdots(f_r^{C_C} L_{h|r}^{C_C})}{\sum_{s_1=1}^{S_1}\sum_{s_2=1}^{S_2}\cdots\sum_{s_C=1}^{S_C}\left(f_{s_1}^{C_1} L_{h|s_1}^{C_1}\right)\left(f_{s_2}^{C_2} L_{h|s_2}^{C_2}\right)\cdots\left(f_{s_C}^{C_C} L_{h|s_C}^{C_C}\right)}. \tag{8}$$

A household would be assumed to have identical behaviors across all C product categories (described by the parameters for segment r) if the posterior probability in Eq. (8) were higher than for any other combination of segments.

3. Data

Information Resources, Inc. (IRI) scanner panel data are used to explore intercategory consumer behavior. The panelists, located in a Chicago suburban area, are tracked over the 112-week period from September 1995 to November 1997. The three product classes used are liquid laundry detergent, paper towels, and margarine. A random sample of 200 households from a total of 752 households making purchases in all three categories is used for analysis. The total number of purchases made by these 200 households is 5728, with 1201 of the purchases for laundry detergent, 2409 for margarine, and 2118 for paper towels. In addition, another sample of 100 households was drawn for the purpose of model validation. These households make 575 laundry detergent purchases, 982 paper towel purchases, and 1130 margarine purchases, for a total of 2687.

[5] There could be a third segment with common parameters across the two categories having three and four segments, and the category with four segments would then have one remaining segment with independent behaviors.

[6] Technically, varying the number of segments within the ICLM model and comparing various specifications with BIC would be a preferred method of determining the number of segments for each product category. We simplified this procedure in order to reduce the computational burden, which is considerable with the amount of data and the number of parameters involved.

Brand names and sizes with 3% or greater market share were retained for analysis. For laundry detergents, the brand names are Ajax, All, Arm & Hammer, Cheer, Era, Surf, Tide, Wisk, XTR11, and Yes. The sizes are 50, 64, 90, 100, 128, and 200 oz. The total number of brand-sizes retained for analysis is 33. For margarine, the brand names retained are Blue Bonnet, Brummel & Brown, Fleischmann, I Can't Believe It's Not Butter, Imperial, Land O' Lakes, Parkay, Promise, and Shedd's Country Crock, and the sizes retained are 16 and 48 oz. The total number of brand-sizes is 13. For paper towels, the brand names are Bounty, Brawny, HiDri, Mardi Gras, Scott, SoDri, Sparkle, and Viva. The sizes are 1- and 3-roll packs. The total number of brand-sizes is 12.

Across all three product categories, price, store feature advertising, and aisle display data are available. To ensure consistency of the price metric across categories, we first expressed prices on a per unit basis (per ounce or per roll) and then standardized the prices within each category so that they have a mean of zero and a standard deviation of one. Notice that standardization of the price variable is reasonable since only the relative prices of alternatives matter. The magnitude of the price coefficient is obviously affected by the standardization, though its importance is not.

To initialize brand and size loyalty variables, 62 weeks' purchases from the sample panelists are used. A total of 5435 purchases were made during this period (1182 laundry detergent purchases, 2212 margarine purchases, and 2041 towel purchases).

4. Results

4.1. Model estimation and validation results

Table 1 shows the fit and forecasting statistics for (i) independent finite mixture logit models applied to the three product categories (labeled Independent Product Category Models), (ii) an ICLM model with one common segment across categories, and (iii) an ICLM model with two common segments across categories. The fit criteria are two versions of BIC, one computed with n being the total number of purchases (5728) and the other with n being the total number of households (200), and the prediction criterion is the validation sample log likelihood. The results show that the ICLM model with one common segment fits and forecasts at least as well as the independent PC models, but that the ICLM model with two common segments is slightly less consistent with the data. In the discussion that follows, we focus on the ICLM model with one common segment on the strength of its fit and forecasting performance shown in Table 1.

Table 2 shows the parameter estimates for the ICLM model with one common segment. Segment 1 is the constrained segment; note that this segment does not have independent marketing mix and loyalty coefficients for the margarine and paper towel categories. Rather, these coefficients are the same as those presented for liquid detergent, up to the scale factor value. More specifically, the price, store feature, aisle display, brand loyalty, and size loyalty coefficients for segment 1 for the margarine data are found by multiplying the respective values for these variables from segment 1 for the liquid detergent data by the relative scale factor for segment 1 for the margarine data. For example, the price coefficient for segment 1 for the margarine data is $-2.73 \times 1.60 = -4.35$, and the price coefficient for segment 1 for the paper towel data is $-2.73 \times 1.27 = -3.46$.

From Table 2, we can see that common segment 1 is very price sensitive for all categories (indeed segment 1 is more price sensitive than the other segments in all three categories)[7] but generally not as promotion sensitive as other segments. Sensitivity to store feature advertising is extremely low for the segment with identical behaviors, and sensitivity to aisle display is also generally somewhat lower than other segments, though aisle display for margarine purchases is an exception.[8] Segment 1 is generally less brand and size loyal than other segments.

[7] About 12% of households are shown in Table 2 to have a significant positive price coefficient for paper towels. This small segment of consumers may have strong preferences for premium brands that are explained better by the price variable than by the brand-specific constants. Alternatively, the segment might be so small that parameter estimates are not reliable. An option in such cases is to constrain the price coefficients to non-negative values and see the impact on goodness of fit.

[8] The different pattern of aisle display sensitivities for margarine could be due to the requirement that margarine must be refrigerated, and hence the nature of aisle displays must be somewhat different from that of laundry detergent and paper towels.

Table 1
Fit statistics for different model specifications (estimation sample: 200 households, 5728 total purchases — 1201 liquid detergent, 2409 margarine, 2118 paper towels; validation sample: 100 households, 2687 total purchases — 575 liquid detergent, 1130 margarine, 982 paper towels)

Model[a]	# Parameters	Log L (est.)	BIC	BIC (200)[b]	Log L (val.)
Independent Product Category Models (PC)	124	– 5980	13032	12616	– 2562
ICLM — 1 common segment	116	– 5985	**12974**	**12585**	**– 2547**
ICLM — 2 common segments	108	– 6054	13042	12680	– 2571

[a] All models are specified to have two segments for laundry detergent, three segments for paper towels, and three segments for margarine, on the basis of BIC.

[b] BIC (200) assumes $n = 200$ (the number of households) rather than the number of purchases (5728).

The findings regarding the marketing mix responses of households with identical vs. independent behaviors are generally confirmed by Table 3, which shows the price and promotion elasticities of segments for one randomly chosen brand in each product category.[9] Common segment 1 is still more price sensitive than most segments (segment 2 for the margarine category is an exception), but it is now also quite sensitive to promotions in the margarine and paper towel categories. (Table 2 showed that segment 1 was not at all sensitive to store feature advertising and, compared to the independent segments, less sensitive to aisle displays except for margarine.) The promotional responses in Table 3 are computed assuming the target brand has a store feature advertisement *and* an aisle display, so the larger than expected promotional elasticities of segment 1 for margarine and paper towels are likely due to the influence of aisle display rather than store feature advertising. In addition, we note that elasticities depend on many factors, including the market share of the target brand (e.g., Guadagni & Little, 1983) and all the other parameters in the choice model, so it is not surprising that there are some differences between the pattern of the price and promotion coefficients in Table 2 and the pattern of elasticities in Table 3.[10] All things considered, however, there is a fair amount of consistency in the pattern of the price and promotion coefficients and elasticities presented in Tables 2 and 3.

Table 4 shows the sizes of segments with identical behaviors across product categories. These are computed from the segment weights appearing at the bottom of Table 2. For example, the probability that a household belongs to common segment 1 for all three product categories is $0.43 \times 0.29 \times 0.40 = 0.05$, which appears in the first row of Table 4.[11] Thus, 5% of households have identical behaviors in all three product categories. As we saw from looking at the parameter estimates of Table 2, the margarine category is somewhat different from the other two and is primarily responsible for the fairly small number of households having identical behaviors across all three categories. In contrast, over 12% of households have identical behaviors in the liquid laundry detergent and paper towel categories, which are more similar products in the sense that they are both inedible cleaning products (though they are still independent products in that they are not complements or substitutes). Overall, about 32% of households have identical behaviors in at least two of the three product categories, according to the ICLM model with one common segment.

Table 5 shows that the 32% of households with identical behaviors in at least two product categories (determined by posterior assignment — see Eq. (8)) tend to be lighter users than the households with independent behaviors across categories. Though segment 1 comprises 32% of the sample, these households purchase 26%, 31%, and 22% of the liquid detergent, margarine, and paper towels, respectively.

[9] We compute short-term price elasticities and promotional responses following the procedures described by Guadagni and Little (1983, p. 230).

[10] We also note that the standardization of prices could affect the elasticity calculation, though we were careful to ensure that a positive increment was added to prices even when the prices were negative.

[11] We obtain exactly the same results when consumers are allocated to segments using posterior probabilities.

Table 2
Intercategory Logit Mixture Model (ICLM) results: one segment common to all three categories (segment 1)

Liquid detergent			Margarine				Paper towels			
Brands	Seg 1	Seg 2	Brands	Seg 1	Seg 2	Seg 3	Brands	Seg 1	Seg 2	Seg 3
Ajax	4.28	0.36	Blue Bonnet	− 2.38	− 1.59	− 0.53	Bounty	0.48	− 0.05	2.25
	(0.29)	(0.22)		(0.24)	(0.23)	(0.18)		(0.21)	(0.15)	(0.20)
All	5.95	0.93	Br & Br	− 7.30	4.63	− 1.69	Brawny	− 1.07	− 0.69	2.91
	(0.16)	(0.17)		(0.38)	(0.15)	(0.44)		(0.19)	(0.17)	(0.25)
Arm & Ham	0.15	− 0.20	Fleischmann	− 7.67	3.29	− 0.42	Hidri	− 4.50	− 1.84	0.55
	(0.30)	(0.24)		(0.49)	(0.21)	(0.19)		(0.33)	(0.45)	(0.94)
Cheer	2.79	1.45	Can’t Believe	6.55	4.75	− 0.25	Mardi Gras	− 4.23	− 0.78	− 2.41
	(0.37)	(0.20)		(0.18)	(0.20)	(0.17)		(0.15)	(0.14)	(0.99)
Era	1.11	0.58	Imperial	− 2.30	− 0.76	− 0.25	Scott	− 1.84	− 0.54	− 0.05
	(0.33)	(0.19)		(0.16)	(0.16)	(0.12)		(0.28)	(0.15)	(0.25)
Surf	2.91	1.37	Land O’ Lake	0.08	1.88	− 0.27	SoDri	− 6.87	− 1.14	10.42
	(0.32)	(0.20)		(0.30)	(0.31)	(0.16)		(0.14)	(0.20)	(0.31)
Tide	5.52	1.94	Parkay	− 0.82	1.99	− 0.57	Sparkle	− 4.53	− 1.78	6.01
	(0.18)	(0.14)		(0.33)	(0.23)	(0.19)		(0.23)	(0.33)	(0.54)
Wisk	4.75	1.80	Promise	2.36	3.99	− 0.52	Viva	[0.00]	[0.00]	[0.00]
	(0.23)	(0.15)		(0.35)	(0.14)	(0.17)				
XTR11	2.31	− 0.95	Shedd’s	[0.00]	[0.00]	[0.00]				
	(0.21)	(0.26)								
Yes	[0.00]	[0.00]								
Sizes			Sizes				Sizes			
50 oz.	12.02	2.23	16 oz.	3.36	5.61	0.09	1 roll	4.22	− 0.02	− 6.41
	(0.27)	(0.14)		(0.17)	(0.53)	(0.14)		(0.28)	(0.06)	(0.56)
64 oz.	6.55	1.10	48 oz.	[0.00]	[0.00]	[0.00]	3 rolls	[0.00]	[0.00]	[0.00]
	(0.20)	(0.19)								
90 oz.	9.75	0.31								
	(0.48)	(0.36)								
100 oz.	11.72	1.53								
	(0.14)	(0.12)								
128 oz.	6.35	0.96								
	(0.15)	(0.16)								
200 oz.	0.00	0.00								
Scale factor	[1.00]	[1.00]	Scale factor	1.60	[1.00]	[1.00]	Scale factor	1.27	[1.00]	[1.00]
				(0.03)				(0.03)		
Price	− 2.73	− 1.16	Price	[− 4.35]	− 3.31	− 0.16	Price	[− 3.46]	− 0.08	3.56
	(0.03)	(0.06)			(0.08)	(0.06)			(0.04)	(0.09)
Store feature	0.02	1.38	Store feature	[0.03]	− 0.17	0.68	Store feature	[0.02]	0.70	1.80
	(0.04)	(0.14)			(0.24)	(0.16)			(0.16)	(0.41)
Aisle display	0.88	1.19	Aisle display	[1.40]	0.67	0.39	Aisle display	[1.11]	1.72	1.24
	(0.07)	(0.13)			(0.19)	(0.16)			(0.13)	(0.40)
Brand loyalty	2.18	4.49	Brand loyalty	[3.47]	4.62	4.83	Brand loyalty	[2.76]	4.52	1.98
	(0.11)	(0.17)			(0.19)	(0.14)			(0.13)	(0.30)
Size loyalty	0.92	2.99	Size loyalty	[1.47]	2.50	2.80	Size loyalty	[1.17]	3.22	5.53
	(0.11)	(0.17)			(0.56)	(0.21)			(0.20)	(0.83)
λ_B	0.75		λ_B		0.88		λ_B		0.80	
λ_S	0.78		λ_S		0.80		λ_S		0.71	
Weights	0.43	0.57	Weights	0.29	0.33	0.38	Weights	0.40	0.48	0.12

Standard errors in parentheses.
Numbers in brackets are derived/constrained parameter estimates.

Table 3
Price elasticities and promotional responses from ICLM (1 common segment) for one randomly chosen brand, by segment and product category

	Laundry detergent			Margarine			Paper towels		
	Price	Prom	Wt	Price	Prom	Wt	Price	Prom	Wt
Segment 1 (C)	− 2.24	1.40	0.43	− 2.18	0.84	0.29	− 1.89	0.80	0.40
Segment 2	− 0.85	7.77	0.57	− 2.21	0.32	0.33	− 0.03	0.70	0.48
Segment 3	–	–	–	− 0.09	1.19	0.38	0.97	0.72	0.12

Thus, those with common behaviors purchase fewer rolls of towels and marginally less laundry detergent but the same amount of margarine as those with independent behaviors across categories.

Table 6 further profiles the households with identical vs. independent behaviors across product categories using logit analysis. The dependent variable is a 0/1 variable indicating whether the household has identical behaviors in at least two product categories. The identification of these households was done using the posterior probabilities described in Eq. (8). The predictors consist of demographic and shopping behavior variables, which are treated as intervally scaled variables. The demographic variables include family size, income, male age, female age, male education, and female education. The shopping behavior variables include the average number of shopping trips per week and the average dollar amount spent on each trip[12] for the entire shopping basket, not just the three product categories examined in Table 5.

The results in Table 6 show that those with common behaviors as described by segment 1 tend to have larger families and marginally lower incomes ($P = 0.0966$), and they make fewer shopping trips and spend less money per trip. This analysis generalizes the findings of Table 5, which shows that the households with identical behaviors are lighter users in two of the three product categories, to show that these households are also lighter users in other product categories as well. The profile of this segment is consistent with the greater price sensitivity and lower loyalty observed for this segment as well. Perhaps the segment with identical behaviors is more prone to using the heuristic “buy the cheapest brand” given the larger families and marginally lower incomes of this segment.

5. Summary, implications, and suggestions for future research

Our research questions and findings are as follows:

RQ1. Are there segments of households whose choice behaviors are identical across product categories?

RQ2. If so, what are the relative sizes of segments whose behaviors are identical across categories vs. independent across categories?

Our intercategory logit mixture model, which imposed behavioral constraints across product categories, could not be rejected on the basis of fit or forecasting performance. In fact, its performance was slightly better overall than that of independent product category models. However, the segment with identical behaviors in all three categories comprises only 5% of the sample households. More commonly, households had identical behaviors in the laundry detergent and paper towel categories but different behaviors in the

Table 4
Sizes of segments with identical behaviors across product categories

Identical behaviors for...	ICLM—1 common segment
Laundry, towels, margarine	0.05
Laundry, towels	0.12
Laundry, margarine	0.08
Towels, margarine	0.07
Total identical behaviors	0.32
No identical behaviors	0.68
Total	1.00

[12] This variable was divided by 10 to improve the scaling of the variables.

Table 5
Usage rates, by segment and product category

Data	Segment 1 identical behaviors 64 households (32%)	Segment 2 independent behaviors 136 households (68%)	P-value (H_0: $\pi = 0.32$)
Liquid detergent	0.26	0.74	0.0788
Margarine	0.31	0.69	0.7617
Paper towels	0.22	0.78	0.0024

margarine category. This suggests that the extent of identical choice behaviors across categories depends on the similarity of the product categories, that households will not necessarily use identical decision heuristics in completely unrelated product categories. Laundry detergent and paper towels are both inedible cleaning-related products, whereas margarine is a perishable, edible product. Overall, about 32% of households had identical choice behaviors in at least two of the three product categories studied. There are two major implications of these results, one for marketing scientists and consumer behavior scholars and the other for practitioners.

First, it may be possible to develop empirical generalizations (Bass & Wind, 1995) or a theory of consumer brand choice behavior for *complementary* or even some *independent* product categories, whereas most research now focuses on consumer behavior among substitutes within a product category. That is, it may be possible to infer fundamental roles that price, promotion, and loyalty play in explaining consumer brand choice behavior across related product categories. Previously, this has been elusive since parameter estimates across categories may appear to be different because (i) households have different degrees of error in their choices in different product categories, and/or (ii) price or promotion-sensitive households may be heavy users in some categories but light users in others. This may lead to the conclusion that price or promotion sensitivity varies across product categories when in fact there is a significant segment of households with identical price sensitivities across product categories.

Second, manufacturers and retailers could begin to conceptualize their problem as one that seeks to manage across product categories in addition to managing at the brand or category level. The results of our study suggest that a manufacturer of products in related product categories might be able to use one stimulus to produce the same responses in multiple product categories simultaneously, at least for some households. For example, a manufacturer of laundry detergent, all-fabric bleach, and fabric softeners may identify a segment of households with identical and strong responses to price and/or promotion in the three categories. To encourage these households to purchase in multiple categories on a given purchase occasion, manufacturers could include on-package coupons for products in the other categories (e.g., include a coupon for all-fabric bleach or fabric softener on the laundry detergent package). Perhaps the size of a traditionally effective promotion on one of the products could be split so that the household gets the full amount of the savings only if it purchases in multiple product categories. It may also be possible in some situations to coordinate the sizes of the promoted items so that interpurchase intervals are similar, which could facilitate this promotional strategy. This would be especially appealing if the segment with identical behaviors happened to prefer smaller or larger sizes consistently across product categories (our segment with identical behaviors tended to prefer smaller sizes). Obviously, product bundling strategies might benefit from this type of analysis as well (Russell & Kamakura, 1997) if the manufacturer can identify when a segment of households is *not* likely to purchase another of the company's products in a complementary product category. For example, if the segment with common choice behaviors across segments had a high valuation (brand-specific con-

Table 6
Demographic characteristics and shopping behaviors of consumers with identical behaviors across at least two categories: logit results (baseline is segment with independent behaviors across product categories)

Variable	Coefficients	S.E.	P-value
Family size	0.69	0.15	0.0000
Income	− 0.10	0.08	0.0966
Male age	0.21	0.21	0.1567
Female age	− 0.28	0.23	0.1167
Male education	− 0.15	0.15	0.1591
Female education	0.15	0.19	0.2165
Trips/week	− 0.54	0.25	0.0137
$ spent/trip	− 0.25	0.09	0.0028

stant) for the manufacturer's brand in one category but a low valuation for the same manufacturer's brand in another category, a bundling strategy might be appropriate.

Retailers could begin to think about customer-based coordination of product assortment, price and promotion strategies across product categories in addition to within a product category in order to maximize profits at the store level. Conceptually, this goes a step beyond category management, which involves managing product categories as business units and identifying the optimal product mix that demographics indicate customers wish to purchase (Nielsen, 1992). For example, if a retailer could identify a segment of households with identical choice behaviors across related products (e.g., soft drinks and snacks), it could coordinate product assortment, pricing, and promotion strategies across categories (as described above), even if the promoted products are not manufactured by the same company. Instead, the retailer could choose to coordinate target products across categories that maximize its own profit margins. Likewise, retailers could carry product assortments and conduct promotions for the other brands in the affected categories accordingly to facilitate sales of the target items.

RQ3. Also, how do segments of households with behaviors identical across categories differ from seg ments with behaviors independent across categories? Are their demographic characteristics different? Do their shopping behaviors differ?

Households with identical behaviors across segments tend to be lighter users, while the segment with independent behaviors across categories is composed of heavier users. This is the case not only with two of the three product categories examined in this study but also with the households' entire shopping basket. Households with identical behaviors are found to have more sensitivity to price, less sensitivity to store feature advertising, and weaker loyalty for both brand names and sizes.

The demographic characteristics of the households belonging to the segment with identical behaviors across two or more categories are quite consistent with the revealed responses of those households. The households tended to have larger families but marginally lower incomes, and they shopped less frequently and bought less when they did shop. This demographic profile is consistent with the high price sensitivity of the households. In addition, it appears that these households do not fit the profile of a "smart" shopper who would scan store feature ads prior to shopping—larger families and lower incomes (possibly correlated with lower education) might suggest less time and inclination for "smart" shopping. Indeed, these households showed no sensitivity to store feature advertising. In any case, households with larger families and marginally lower incomes have higher price sensitivity and lower brand loyalty, suggesting that they are prone to buying the cheapest brand. This finding is also consistent with Bell and Lattin's (1998) theory that large shopping basket customers should be less price responsive than small shopping basket customers. Ainslie and Rossi (1998) also find that increases in total expenditures lower price sensitivity.

Manufacturers and retailers could use the demographic and shopping behavior profiles of households with identical behaviors across categories to better identify and reach these households with promotions. In fact, demographic and shopping variables could also be included in the intercategory logit mixture model as concomitant variables to better profile the segment or segments with identical behaviors across categories (e.g., Gupta & Chintagunta, 1994; Kamakura, Wedel, & Agrawal, 1994). We leave this as a suggestion for future research in the area of intercategory choice behavior.

Several other natural extensions are possible for future research. The three product categories studied here are very similar in the sense that they are all low-involvement products. To improve the generalizability of the findings, it would be necessary to look at more and different categories. In addition, it would be interesting to see if the extent of identical behaviors increases when more similar product categories are examined. Examination of behaviors for substitute and complementary product categories would also be very interesting. This study relies on independent (e.g., neither substitute nor complementary) product categories.

In this paper, we have focused on household brand choice behavior. Other household behaviors that could be assessed across product categories are purchase incidence (product category purchase), quantity purchased, and consumption or usage rates. For example, Bucklin et al. (1998) present a mixture model for purchase incidence, brand choice, and quantity purchased. One could test the relative efficacy of such models estimated one product category at a time with an intercategory model describing those same behaviors for an even richer portrait of household choice and consumption behavior across product categories.

Conceptually, intercategory models can be extended to formulate inter-environment models wherein it may be possible to assess the extent of communality between household choice and consumption behaviors across different shopping environments (e.g., online vs. traditional shopping channels). Conceptually, it is also possible to combine inter-environment models with intercategory models to assess communality between household choice and consumption behaviors across product categories and shopping environments, for even richer portraits of household choice and consumption behaviors. Thus, the intercategory model described in this paper permits several exciting and potentially promising research directions to enhance our understanding of consumer behavior. We hope our efforts will motivate such work.

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