Observed and Unobserved Preference Heterogeneity in Brand-Choice Models

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This paper extends the scanner-based choice literature by explicitly incorporating individual-level brand-preference data. We illustrate our model using a unique data set that combines survey and scanner data collected from the same individuals.

The addition of individual-specific brand-preference information significantly improves fit and prediction. Furthermore, this "observed" heterogeneity better explains choice than does "unobserved" heterogeneity in the standard scanner model's parameters. More importantly, we find that the standard model underestimates the importance of consumers' brand preferences and overestimates both brand loyalties and price sensitivities. Brand loyalty is overestimated because models without preference information confound state dependence, heterogeneity, and preference effects. Price sensitivities are inflated because the "average" preference-based consumer is implicitly assumed to be more willing to switch from his preferred brand than is the "real" preference-based consumer. Further, standard models overestimate the heterogeneity in price and loyalty sensitivities and misidentify both price- and loyalty-sensitive consumers.

The managerial implications of our findings and the applicability of our methodology when survey data are collected infrequently and for only a subsample of consumers are pursued. We demonstrate that even under these circumstances better populationwide pricing and promotion decisions are identified and more accurate targeting results.

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Introduction

Brand strategy and tactic decisions are typically based on an understanding of how consumer choice is influenced by marketing mix elements controlled by the firm. Since the pioneering work of Guadagni and Little (1983), brand-choice models calibrated on scanner data have increased our understanding of how these controllable factors affect choice in frequently purchased product classes. It also is recognized that consumers are heterogeneous in their response to these factors, and that accounting for this is critical to uncovering consistent and unbiased effects. Data limitations, however, have precluded individual consumer-level parameter estimation. Hence, researchers have utilized parametric assumptions (i.e., a mixing distribution) to attack this issue. The most popular approaches use a multivariate normal distribution (e.g., Gönül and Srinivasan 1993, Allenby and Rossi 1999) or a discrete point mass density (e.g., Kamakura and Russell 1989, Chintagunta and Gupta 1994). Andrews et al. (2002) show that either approach improves fit and results in better parameter recovery.[1]

Another reason for parameter heterogeneity, particularly in the brand-specific constants, is to acknowledge that differences exist in the underlying preferences consumers have for the various brands. A stochastic implementation of heterogeneity in these constants induces a particular pattern of brand-preference differences across consumers. Thus, researchers implicitly rely on an accurate mapping of the true-preference heterogeneity to this stochastic counterpart. If this mapping is inadequate, the estimates obtained will not reflect true preferences well.

This paper deals with a simple yet powerful question. What if we had information about the preferences of individual consumers and, hence, the actual distribution of their preferences? Such "observed" preference information should allow a better understanding of the nature of consumer heterogeneity, better explain observed choice, and uncover possible biases in parameter estimates. Consequently, better managerial decisions should result. This paper

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[1] The substantive importance of incorporating heterogeneity into choice models is evidenced by recent research that has used such models outside typical scanner data applications to study novel issues like the dynamic evolution of preferences (Liechty et al. 2005), strategic marketing mix allocation across countries (Chintagunta and Desiraju 2005), and the customization of online promotions (Zhang and Krishnamurthi 2004).

addresses these very issues. Using a unique data set that contains both scanner panel data and survey-based brand preferences from the same individuals, we construct and implement a series of discrete-choice models that explore the benefits of observed and unobserved heterogeneity specifications.

Four key findings are presented. First, including stated individual-level preferences in a brand-choice specification results in a fit that is substantially better than when unobserved heterogeneity alone is modeled. Out-of-sample prediction also is improved. Unobserved heterogeneity fails to adequately capture underlying preferences and, hence, performs poorly when compared to models that incorporate stated brand preferences. Second, and more importantly, the omission of preference information in brand-choice models induces systematic biases in the price and loyalty parameter estimates. These biases are both statistically and economically significant. This has important implications for pricing and promotion decisions which we illustrate using counterfactual experiments. Third, in the absence of stated preference information, the heterogeneity in the price and loyalty parameters is exaggerated. Households are more similar in their response to past purchases and prices than traditional heterogeneity models imply. Since the degree of heterogeneity in the consumer base reflects the potential for segmentation, this finding has important price discrimination implications. Finally, upon the inclusion of stated preference information, *different* households are found to lie at the extremes of the price and loyalty heterogeneity distributions. This suggests that any household-level targeting would be flawed without the inclusion of stated preferences.

The paper proceeds as follows. We start with a brief review of the consumer utility and brand-choice literature which leads to a set of models that we later evaluate empirically. Next, we discuss the impact the inclusion of observed preferences may have on the choice model. Our data set is then described and the constructs used in the analysis are operationalized. We next estimate our models and compare their fits, predictive abilities, and parameter estimates. A discussion of our key findings and their managerial implications follows. The practical application of our methodology also is discussed and illustrated. We close with a summary.

Heterogeneous Brand-Choice Models

The utility maximizing individual evaluates the utilities of the various brands within a product class, $U(\text{brand}) = f(\text{brand value, value of all other goods})$, and, subject to a budget constraint, chooses the brand that maximizes this utility (Rosen 1974). Assuming additive separability, the utility of brand j to consumer i at time t is depicted as a benefit/cost trade-off

$$U_{ijt} = V_{ijt} - f_p(p_{ijt}), \qquad (1)$$

where V_{ijt} equals the "total brand value" of brand j to consumer i at time t and p_{ijt} is the price of brand j faced by consumer i at time t.

Total brand value V_{ijt} clearly depends on the consumer's perceptions of and reactions to the characteristics of the brand and its marketing environment. As such, the consumer's perceptions of the attribute content of each brand and the relative importances of these attributes are central to total brand value (Lancaster 1966, Fishbein 1967). This notion leads to an "intrinsic brand value" (IV_{ij}) which reflects a particular consumer's preference for a given brand. Total brand value also reflects past consumption-related factors such as loyalty and state dependence (Massey et al. 1970). Moreover, total brand value is also affected by the brand's promotional activity which influences awareness and so on.

The key issue in this paper concerns how individual-specific intrinsic brand value (IV_{ij}) has been measured previously and whether this can be improved upon. Better specification and measurement of intrinsic brand value (and, hence, also total brand value V_{ijt}) should allow more accurate insights into how choice is influenced by the factors that constitute brand value as well as by price.

Brand-Choice Model with Traditional Heterogeneity (TH)

The scanner-based brand-choice literature utilizes time series data of individual level consumer choices to measure the influences of price and other variables on these purchases. The traditional heterogeneous brand-choice model (TH) starts with the utility function specification

$$U_{ijt} = \tilde{\alpha}_{ij} + \boldsymbol{\beta}_i' \mathbf{x}_{ijt} - \theta_i p_{ijt} + \varepsilon_{ijt}. \qquad (2)$$

The intrinsic brand value IV_{ij} that consumer i places on brand j is proxied for by brand-specific constants $\tilde{\alpha}_{ij}$. The vector $\mathbf{x}_{ijt}$ is composed of the other variables—previous purchases (commonly referred to as loyalty) and promotions—which also impact the total brand value of brand j at time t. That is, total brand value $V_{ijt} = \tilde{\alpha}_{ijt} + \boldsymbol{\beta}_i' \mathbf{x}_{ijt}$. Also, p_{jt} is the price paid by consumer i for brand j at time t and ε_{ijt} is a stochastic component that is usually assumed to be distributed i.i.d. Gumbel. It follows that the probability that individual i chooses brand j at time t is of the well-known conditional logit form. As discussed previously, a mixing distribution on the parameters $\tilde{\alpha}_{ij}$, $\boldsymbol{\beta}_i$, and θ_i is used to represent "unobserved" heterogeneity across individuals. In addition, we allow the individual-specific parameters to be functions of demographics. Details are provided below.

Brand-Choice Model with Complete Heterogeneity (CH)

The complete heterogeneity (CH) model we propose extends the traditional heterogeneity framework by including a stated-preference measure (i.e., "observed" heterogeneity) in the utility function. In other words, we define intrinsic brand value as $\text{IV}_{ij} = \alpha_{ij} + \omega_i \text{PREF}_{ij}$, where PREF_{ij} denotes the preference of consumer i for brand j. Hence,

$$U_{ijt} = \alpha_{ij} + \omega_i \text{PREF}_{ij} + \boldsymbol{\beta}_i' \mathbf{x}_{ijt} - \theta_i p_{ijt} + \varepsilon_{ijt}. \qquad (3)$$

In addition to allowing for unobserved heterogeneity, we also let the parameters in both the TH and CH models depend upon a second type of "observed" heterogeneity—household demographics ($\mathbf{z}_i$). Correspondingly, the model parameters are defined as

$$\begin{bmatrix} \alpha_{ij} \\ \omega_i \\ \boldsymbol{\beta}_i \\ \theta_i \end{bmatrix} = \begin{bmatrix} \alpha_j \\ \omega \\ \boldsymbol{\beta} \\ \theta \end{bmatrix} + \begin{bmatrix} \boldsymbol{\delta}'^{(\alpha)} \\ \boldsymbol{\delta}'^{(\omega)} \\ \boldsymbol{\delta}'^{(\beta)} \\ \boldsymbol{\delta}'^{(\theta)} \end{bmatrix} \mathbf{z}_i + \begin{bmatrix} \eta_{ij}^{(\alpha)} \\ \eta_i^{(\omega)} \\ \boldsymbol{\eta}_i^{(\beta)} \\ \eta_i^{(\theta)} \end{bmatrix}, \qquad (4)$$

where the $\boldsymbol{\eta}$ are random deviates that are jointly distributed multivariate normal with mean zero and variance-covariance matrix $\boldsymbol{\Sigma}_{\boldsymbol{\eta}}$. Thus, the CH specification outlined by Equations (3) and (4) accounts for multiple sources of heterogeneity: (i) observed preference heterogeneity captured via stated preferences, and (ii) heterogeneity in the effects of all variables (including stated preferences) via both unobserved and observed demographic parameter components. Thus, the model allows consumers to not only react differently to marketing stimuli but also to have different preferences and have these preferences impact choices idiosyncratically.[2]

The traditional heterogeneity (TH) model ignores the effect of stated-preference information but allows for both unobserved *and* observed demographics heterogeneity in the parameters. In sum, TH is a restricted version of CH with $\omega_i = 0$ for all i. Hence, a comparison of these models boils down to a question of whether simply modeling heterogeneity in the brand-specific constants and the parameters of the other variables as in TH adequately compensates for a lack of knowledge about unmeasured individual preferences and the unmeasured impact these preferences have on choice. In particular, the brand-specific constants in TH recover the average preferences across people, and if preferences have a fairly predictable distribution across people, overlaying a heterogeneity distribution on these constants will be of help.

Brand-Choice Model with Only Observed Heterogeneity (OH)

A parameter homogeneity assumption in model (3) allows us to further focus on the importance of including stated-preference data. This OH model does not allow a mixing distribution on any of the parameters. That is, no unobserved heterogeneity is modeled (i.e., in Equation (4) all the $\boldsymbol{\eta}$ are set to zero).

Why Include Observed Preference Heterogeneity?

Fit and Prediction

The rationale for including survey-based individual specific preferences in brand-choice models stems from the fact that they should more accurately reflect household cross-sectional differences. Their inclusion allows us to more accurately exploit the "panel" nature of scanner data and, thereby, permits better measurement of the effects of time-varying marketing activities such as price and promotion. As a result, we expect not only better fit and prediction but also more importantly cleaner, more precise estimates of how intrinsic brand value, brand loyalty, and price influence choice. In what follows we delineate the impact that the inclusion of preferences might have on these three influences.

Intrinsic Brand Value and the Brand Specific Constants

The extant literature posits that the brand-specific constants ($\tilde{\alpha}_{ij}$) included in the traditional heterogeneity TH utility specification (2) represent the intrinsic values of the brands in question. Clearly, preference heterogeneity is an individual-specific manifestation of this same construct. Equations (2) and (3) highlight the fact that heterogeneity in the brand-specific constants is motivated by differences across people in their brand preferences.[3] In particular, traditional scanner-based brand-choice models characterize a consumer's intrinsic brand values or preferences using his/her string of observed choices and the choices of other consumers (i.e., market share). That is, the estimated individual-specific brand-specific constants ($\tilde{\alpha}_{ij}$ in Equation (2)) are shrinkage estimators (with shrinkage toward the preferences of the "average" consumer).[4] As such, they underestimate the

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[2] Our model does not, however, account for the effects of unmeasured brand characteristics (such as weekly changes in shelf space allocation) recently examined by Chintagunta et al. (2005).

[3] This heterogeneity in the brand-specific constants has its roots in the differences that exist across people in how they perceive the attribute levels of each brand and how they relatively value these attributes. This multiattribute perspective provides the impetus for the market structure "choice map" literature (e.g., Kamakura and Russell 1993, Chintagunta 1994, Elrod and Keane 1995).

[4] Such shrinkage is nicely illustrated by a homogeneous choice model with no covariates where the brand-specific constants are simply a direct transformation of the relevant market shares.

true dispersion of preferences in the population. In contrast, with stated preferences there is less reliance on the "average" consumer's preferences and more disperse intrinsic brand values result. This has pricing implications, discussed below.

Brand Loyalty

A past purchase or brand loyalty variable may capture two disparate effects. One effect pertains to state dependence or other temporal reinforcement effects while the other reflects the researcher's learning about the consumer's preference for a brand. Since the complete heterogeneity CH model incorporates stated preferences as well as parameter heterogeneity, the relevance of the brand loyalty variable should be reduced as it now measures only the first of these two effects. As a result, we should expect to see a reduction in the importance of the loyalty variable in explaining choice. If this is indeed the case, then there are important implications for managers seeking to target either loyal, variety-seeking, or new customers.

Price Sensitivity

Price sensitivity reflects the amount of price cut needed to compensate a consumer for switching from his/her most preferred brand to his/her second most (or lower) preferred brand (Nevo 2000). Correspondingly, when individual-level preferences are unknown, estimated price sensitivity relates to the price cut required to cause brand switching by the "average" consumer. These price cuts may be smaller than those required under our model since known individual-specific preferences are more disperse. This reduced-price sensitivity (i.e., a greater price cut is required to cause a switch) should manifest itself via an increase in the joint impact of the constructs which measure intrinsic brand values—the brand-specific constants and observed preferences and/or via a reduced-price coefficient. The net result is a lower overall impact of price changes on consumer choice. This effect is noted but not articulated in the literature (Fader 1993, Erdem 1996, Erdem and Keane 1996).[5]

The inclusion of observed preferences into the utility function also should impact the degree of heterogeneity in the price coefficient. Since our model better accounts for cross-sectional differences, it should facilitate a cleaner estimate of the influence that intertemporal changes in price have on choices. In the absence of explicit preference information, the distribution of the price coefficient picks up some of

the preference differences across individuals, thereby exaggerating the parameter's estimated heterogeneity. In the CH model, however, this problem is mitigated. Consequently, less heterogeneity in the price effect should result. Since this heterogeneity is directly connected to segmentation and price discrimination strategies, such a finding has important implications for managers. By similar logic, the heterogeneity in the loyalty coefficient also should be reduced.

Data

A unique data set obtained from IRI is used to empirically investigate the three models developed above. As is typical of scanner data, it contains consumer demographics and time-series choice data at the individual level along with price and promotion information for the brands within the category analyzed. In addition, for these same individuals, survey data pertaining to brand preferences for each of the brands is present.

The data consists of 620 households randomly dispersed across the United States who made at least four toothpaste purchases during the year analyzed. Inquiries concerning the seven major toothpaste brands were made. These brands—Aim, Arm & Hammer, Aquafresh, Colgate, Crest, Mentadent, and Pepsodent—totaled 86% of U.S. sales at the time. Our measure of observed preference is a one (low) to seven (high) rating of how much each respondent liked each brand.

Toothpaste choices and the price and promotion environment that each respondent witnessed when making these choices were tracked for one year. Choice occasions on an individual basis averaged 9.11 over this period. The $\mathbf{x}_{ijt}$ vector utilized consists of two variables $\{LOY_{ijt}, DISP_{ijt}\}$. The display variable $DISP_{ijt}$ as measured by IRI is a scaled index (between zero and one) of the intensity of display activity for a particular brand and time in the relevant store. We measure brand loyalty LOY_{ijt} as a dummy variable that equals one if brand j was purchased at time $t-1$. Two variables also are used for the observed parameter heterogeneity component $\mathbf{z}_i$ pertaining to demographics. These are family size $FSIZE_i$ and household income $HHINC_i$. As done in most papers, we utilize shelf price inclusive of any temporary price reduction to measure price p_{ijt} rather than using two variables—list price and amount of temporary price reduction.

Table 1 presents basic descriptive statistics related to both the survey and scanner data. The market shares of most brands are in tune with their average preferences. It is noteworthy that Mentadent and Arm & Hammer exhibit a larger variance in preferences. This heterogeneity indicates that to a greater extent than in other brands, there exists a segment

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[5] These papers find that when a more flexible specification is adopted for the intrinsic brand values, the estimated price effect is lowered. While these authors offer a varied set of explanations, our argument offers a simple explanation that is consistent with economic theory.

Table 1   Description of Data—Means and Standard Deviations of Relevant Variables

Variable	Brand						
	Arm & Hammer	Aim	Aquafresh	Colgate	Crest	Mentadent	Pepsodent
Market share							
Mean	0.0667	0.0210	0.1544	0.3158	0.3240	0.1033	0.0148
Price							
Mean	2.7578	1.4379	2.3705	2.5107	2.4387	3.5467	1.3188
Standard deviation	0.1965	0.2096	0.2018	0.2133	0.2137	0.2581	0.0877
Display							
Mean	0.0386	0.0663	0.1145	0.2784	0.1162	0.0996	0.0422
Standard deviation	0.0539	0.0665	0.0615	0.0981	0.0603	0.0783	0.0522
Loyalty							
Mean	0.0681	0.0195	0.1423	0.2828	0.2736	0.0903	0.0136
deviation	0.2520	0.1382	0.3494	0.4504	0.4459	0.2866	0.1160
Liking							
Mean	3.4613	3.2016	4.3032	5.5145	6.0129	4.1871	2.7081
Standard deviation	2.0281	1.8295	2.0261	1.7798	1.5252	2.2038	1.7120
Family size							
Mean	3.1629						
Standard deviation	1.3052						
Income							
Mean	8.0081						
Standard deviation	2.0827						

Notes. The means and standard deviations across the year of scanner data are reported for market share, price, display, and loyalty. The mean and standard deviation for liking, family size, and income are computed across respondents. Liking is measured on a 1 to 7 scale while income is measured using categories (1 = less than $10K, 2 = $10K–$12K, 3 = $12K–$15K, 4 = $15K–$20K, 5 = $20K–$25K, 6 = $25K–$30K, 7 = $35K–$45K, 8 = $45K–$55K, 9 = $55K–$65K, 10 = $65K–$75K, 11 = $75K–$100K, 12 = greater than $100K). Family size is the number of individuals in the household.

of consumers who value these latter two high-priced brands very highly and constitute their core consumers.

The above suggests that there is a reasonable amount of preference heterogeneity in the data. Given the uniqueness of the data set and the focus of this paper, this aspect warrants further elaboration. Figures 1 and 2 highlight various facets of the preference heterogeneity in the consumer base. The histograms in Figure 1 show that different brands have very different preference distributions across consumers. For example, the distributions for Colgate and Crest are skewed towards higher values while preferences for Mentadent are spread rather evenly. Figure 2 shows that in addition different consumers have very different distributions across brands. While some consumers have very strong preferences for a single brand (e.g., panel member 5), others seem to like all brands and, hence, have no strong preference (e.g., panel members 13 or 16). What should be clear from the two figures is that approximating the true distribution of preferences using uninformative parametric (or nonparametric) distributions is a rather difficult task. In particular, the accurate recovery of individual-level preferences of the kind reported in Figure 2, from a consumer's actual string of brand purchases, does not seem likely.
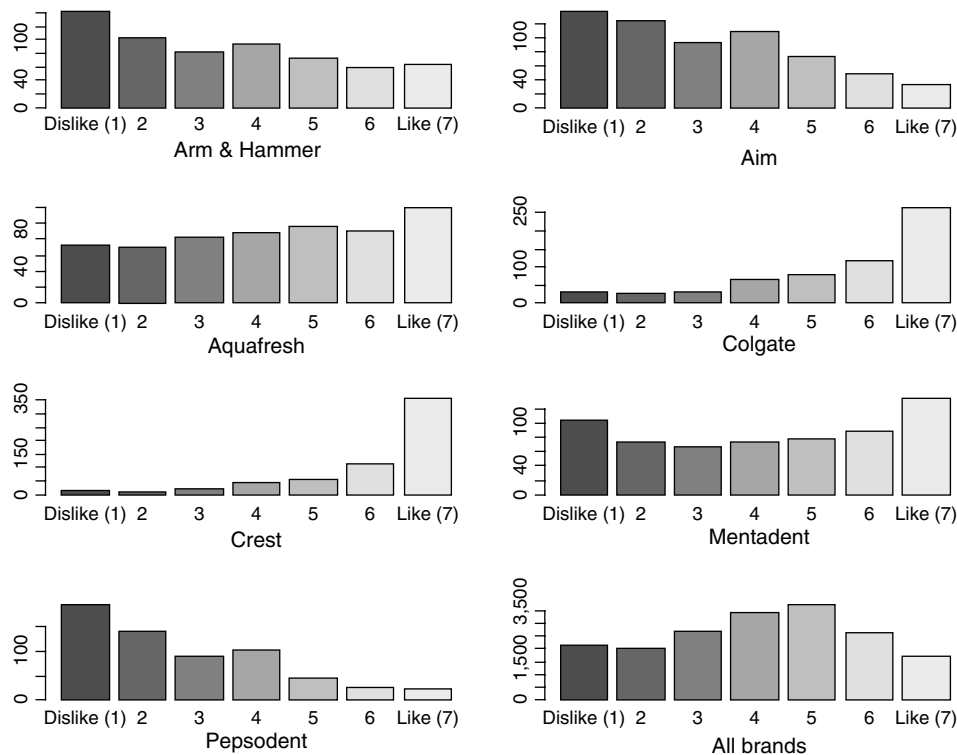
Discussion of Results

We adopt the Bayesian Markov Chain Monte Carlo approach for estimation.[6] Table 2 reports the results. Discussion focuses on a comparison of the proposed model depicting complete heterogeneity (CH, observed heterogeneity in preferences, parameter heterogeneity through demographic and unobserved heterogeneity) and the traditional heterogeneity model (TH, without observed heterogeneity in preferences). In particular, we address the four areas of interest raised earlier concerning how the modeling of observed preference heterogeneity impacts: (i) fit and prediction, (ii) intrinsic brand value and the brand-specific constants, (iii) the relevance of brand loyalty, and (iv) price sensitivity.

Fit and Prediction

The fit results in Table 2 clearly show that a complete specification of heterogeneity (CH) outperforms the traditional heterogeneity (TH) model. Using the harmonic mean approach (Newton and Raftery 1994), the log-marginal likelihoods for the two models are CH $= -3{,}149.1$ and TH $= -3{,}304.6$. While the superiority of CH is not surprising, its magnitude is. Using the comparison criteria proposed by Kass and Raftery

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[6] For details, see Allenby and Rossi (1999) and Wedel et al. (1999).

Figure 1   Distribution of Brand Preferences Across Consumers

(1995), there is *very strong evidence* that the CH model fits the data better than the TH model. Note also that there is significant heterogeneity in the parameters of both models. This implies that preference heterogeneity is only one facet of the inherent heterogeneity in the consumer base, and that modeling heterogeneity in the parameters as done in the existing literature is also important.

The strong superiority in fit of the CH model carries over into out-of-sample prediction. This was evaluated by splitting the data into estimation (60% of households) and validation samples (40%) and reestimating the models on the estimation sample. Then, these parameter estimates were used to predict the choices of both samples. Prediction results are given in Table 3. The CH model has a significantly higher hit rate (percentage of choices predicted accurately) in both the estimation and validation samples (73.59% versus 66.85% for the estimation sample and 68.11% versus 61.8% for the validation sample).
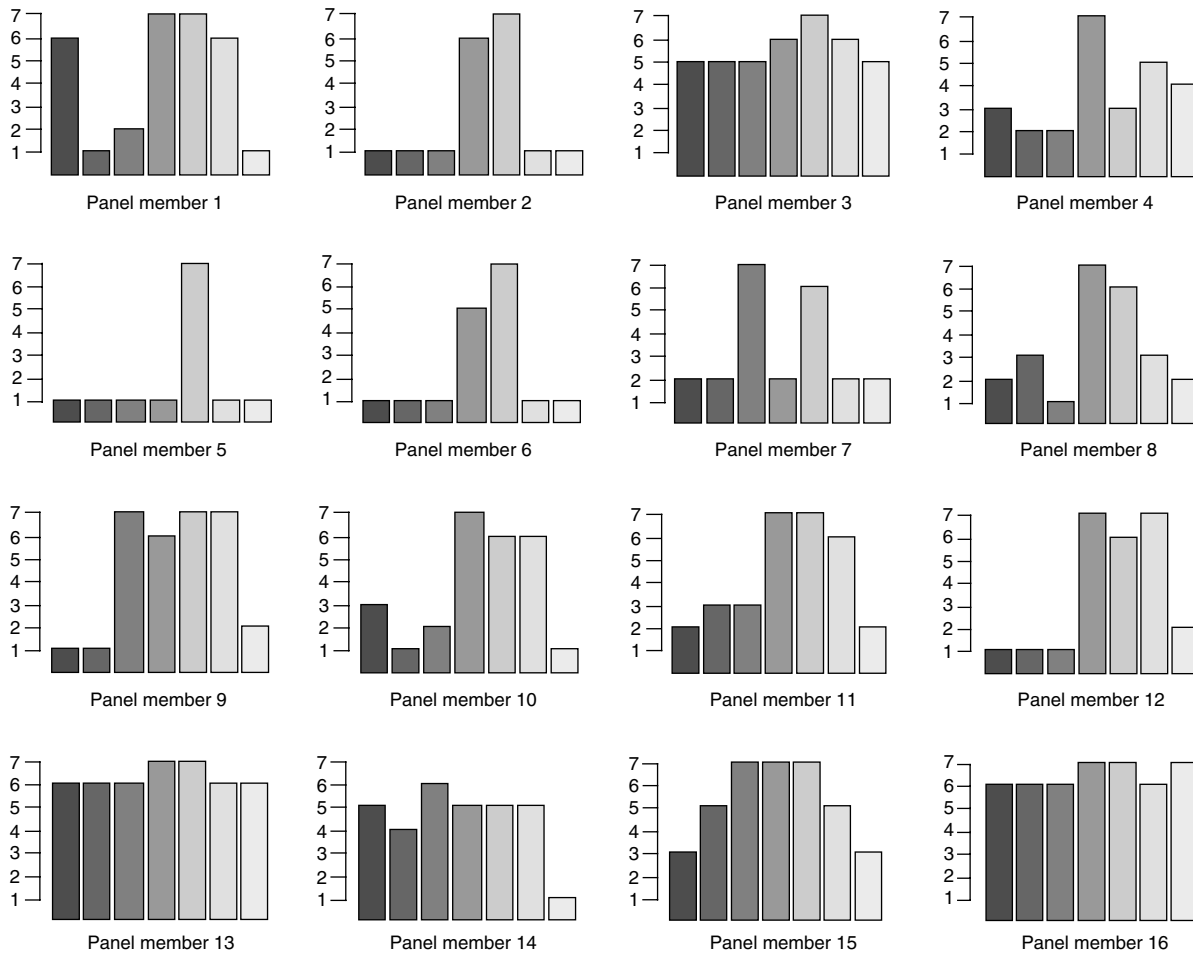
The importance of stated preferences in describing choice is emphasized by a second model comparison. The OH model (a *homogenous* parameter model that includes stated preferences) also provides a better fit (its log marginal likelihood is −3,218.7) than does the TH model. The OH model allows different consumers to have different preferences but does not allow the impact of any variables to be heterogeneous. Alternatively, the TH model does not use individual-level

preference information but does allow individuals to differ in how strongly the observed variables impact choice. Thus, at best the brand-specific constants in TH reflect the product of unobserved variables *and* the unobserved effects these variables have on choice. This means that the unobserved heterogeneity approach is one in which *structure is added* to consumer heterogeneity (via a distribution on the parameters) to better extract information. On the other hand, when preferences are directly included in the framework, *information is added* (via observed preferences) to better understand the nature and structure of utility. As such, our finding suggests that the better measurement of individual-level intrinsic brand values achieved by incorporating observed preferences is more important in explaining choices than allowing for a degree of flexibility in how observed variables such as prices impact choice.

Intrinsic Brand Value and the Brand-Specific Constants

A commonly held belief is that the brand-specific constants of the traditional heterogeneity TH model reflect the intrinsic value of their respective brands (i.e., in Equation (2) $IV_{ij} = \tilde{\alpha}_{ij}$). Our results buoy this belief. The use of stated-preference data in the CH model has a two-fold impact on the brand constants. First, the magnitudes of the constants are altered (see Table 2). This is expected since the constants

Figure 2   Examples of Individual Panel Member Preferences

Note. The bars in the figure depict brands in the following order: Arm & Hammer, Aim, Aquafresh, Colgate, Crest, Mentadent, and Pepsodent.

no longer fully account for the intrinsic brand values (i.e., $IV_{ij} = \alpha_{ij} + \omega_i PREF_{ij}$ under the CH model). More significantly, the variances of these constants fall dramatically. Figure 3 exhibits these effects. These graphs depict the distribution of the individual-level posterior means for the brand constants $\alpha_{ij} = \alpha_j + \boldsymbol{\delta}'^{(\alpha)} \mathbf{z}_i$ under both the TH($\tilde{\alpha}_{ij}$) and CH(α_{ij}) models. Visual examination shows that all of the densities are tighter when stated-preference heterogeneity is added, except for Aim where the density remains essentially the same. To verify that the variances in the posterior densities differ in a statistically significant manner, a Fligner-Killeen[7] test was conducted for each brand constant. All of the pairwise comparisons except that for Aim yield significant differences at the 5% level. In line with our findings on fit and prediction, this reduction in the heterogeneity of the brand constants points to stated preferences as a significant proxy for much of the variation in intrinsic brand values across consumers.

Also in Figure 3 are the posterior distributions of the CH model intrinsic brand values ($IV_{ij} = \alpha_{ij} + \omega_i PREF_{ij}$). The distributions of these IVs are clearly to the right of and more disperse than those of the TH model's brand constants (intrinsic brand values $\tilde{\alpha}_{ij}$). This indicates that larger intrinsic brand values are recovered on average under the CH model, and that this model also uncovers greater heterogeneity in these values. Indeed, Kolmogorov-Smirnov[8] and Fligner-Killeen tests find that all of the distributions differ at the 5% level. As expected, intrinsic brand values are much more important to choice than the unobserved heterogeneity-based estimates lead you to believe. Also, the increased heterogeneity in the IVs is consistent with our earlier discussion of how unobserved heterogeneity-based estimators of brand value are shrunk toward the average. Moreover, the distributions of many of the IVs, in particular those of the smaller brands, appear to be bimodal. This coupled

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[7] The Fligner-Killeen (1976) test is a distribution-free test to compare the scales (variances) of two densities.

[8] The Kolmogorov-Smirnov test (DeGroot 1991) is a nonparametric test that compares the empirical CDFs generated by two independent samples.

Table 2 **Posterior Means for Model Coefficients**

Coefficient	Traditional heterogeneity TH model					Complete heterogeneity CH model				
	Posterior mean*	Constant	Family size	Income	Heterogeneity[†]	Posterior mean*	Constant	Family size	Income	Heterogeneity[†]
Arm & Hammer	**8.0554**	**6.9556** [1.00]	**0.4579** [1.00]	**0.2572** [1.00]	**2.5434**	7.686	5.984 [1.00]	0.099 [1.00]	0.173 [0.93]	0.984
Aim	**0.8136**	**0.3598** [0.94]	**0.3375** [1.00]	**0.0712** [0.70]	**0.9364**	0.982	0.113 [0.91]	−0.046 (0.51)	0.127 [0.58]	1.123
Aquafresh	**8.5362**	**7.4350** [1.00]	**0.3617** [1.00]	**0.3005** [1.00]	**1.9467**	7.048	5.441 [1.00]	0.047 [1.00]	0.182 [0.88]	0.706
Colgate	**10.9792**	**9.6505** [1.00]	**0.4872** [1.00]	**0.3014** [1.00]	**2.7674**	8.340	5.734 [1.00]	0.163 [1.00]	0.261 [1.00]	1.635
Crest	**10.7484**	**9.3039** [1.00]	**0.4760** [1.00]	**0.3194** [1.00]	**2.9607**	7.902	5.315 [1.00]	0.184 [1.00]	0.250 [1.00]	1.846
Mentadent	**11.5186**	**9.8143** [1.00]	**0.5447** [1.00]	**0.4111** [1.00]	**2.8945**	10.185	8.080 [1.00]	0.245 [1.00]	0.166 [0.99]	1.381
Price	**−4.9925**	**−5.1122** (1.00)	**−0.3520** (1.00)	**0.1541** [0.82]	**1.9716**	−4.431	−4.505 (1.00)	−0.322 (1.00)	0.137 [0.98]	1.579
Display	**0.325**	**0.4652** [1.00]	**0.0923** [0.83]	**−0.0523** (0.63)	**0.5156**	0.314	0.329 [1.00]	0.078 [0.86]	−0.031 (0.74)	0.598
Loyalty	**0.7932**	**1.6142** [1.00]	**0.0029** [0.49]	**−0.0965** (0.98)	**0.8848**	0.504	0.782 [1.00]	−0.004 (0.72)	−0.033 (0.83)	0.665
Liking						0.936	1.188 [1.00]	−0.032 (0.93)	−0.019 (0.79)	0.480
Ln marginal likelihood	**−3,304.6**					−3,149.1				

[†]Unobserved heterogeneity is measured by the posterior mean of the square root of the diagonal elements of Σ_{η} (Rossi et al. 1996).
*Posterior means are computed as the average across consumers of the total posterior effects. For example, the posterior mean for price is $(1/N)\sum_{i=1}^{N}\{\theta + \delta'^{(\theta)}z_i\}$. All means are significantly different from zero.
[ ] Indicates probability that coefficient is positive.
( ) Indicates probability that coefficient is negative.

with the information provided earlier in Figures 1 and 2 highlight the reason it is difficult for the TH model to recover the true underlying distribution of preferences.

Brand Loyalty
Figure 4 and Table 2 show the impact that stated-preference heterogeneity has on the brand loyalty coefficients. As expected, because preferences are directly

utilized, the impact of the loyalty variable on choice is reduced under the CH model relative to that under the TH model—the loyalty parameter has a smaller mean and variance. The fact that loyalty remains significant is important and echoes Keane's (1997) finding that even with very rich specifications for heterogeneity, strong loyalty effects remain.

Importantly, the two models identify different households as loyal or variety seeking (i.e., have a negative $\beta_i^{(LOY)}$). To illustrate this, we ranked households using the mean of their posterior loyalty coefficient and examined the concordance of the top 10% (loyals) and bottom 10% (variety seekers) of households. The concordance is only 40%, implying that 60% of the consumers classified as extremely loyal (or variety seeking) by one model are not considered to be so by the other model.

The managerial import of this segmentation finding as well as the CH model's smaller loyalty parameter in general is critical. If, for example, a supermarket is giving away free samples or coupons to households identified using the traditional TH model with the hope of inducing trial and subsequent repurchase, it is likely targeting many wrong households.
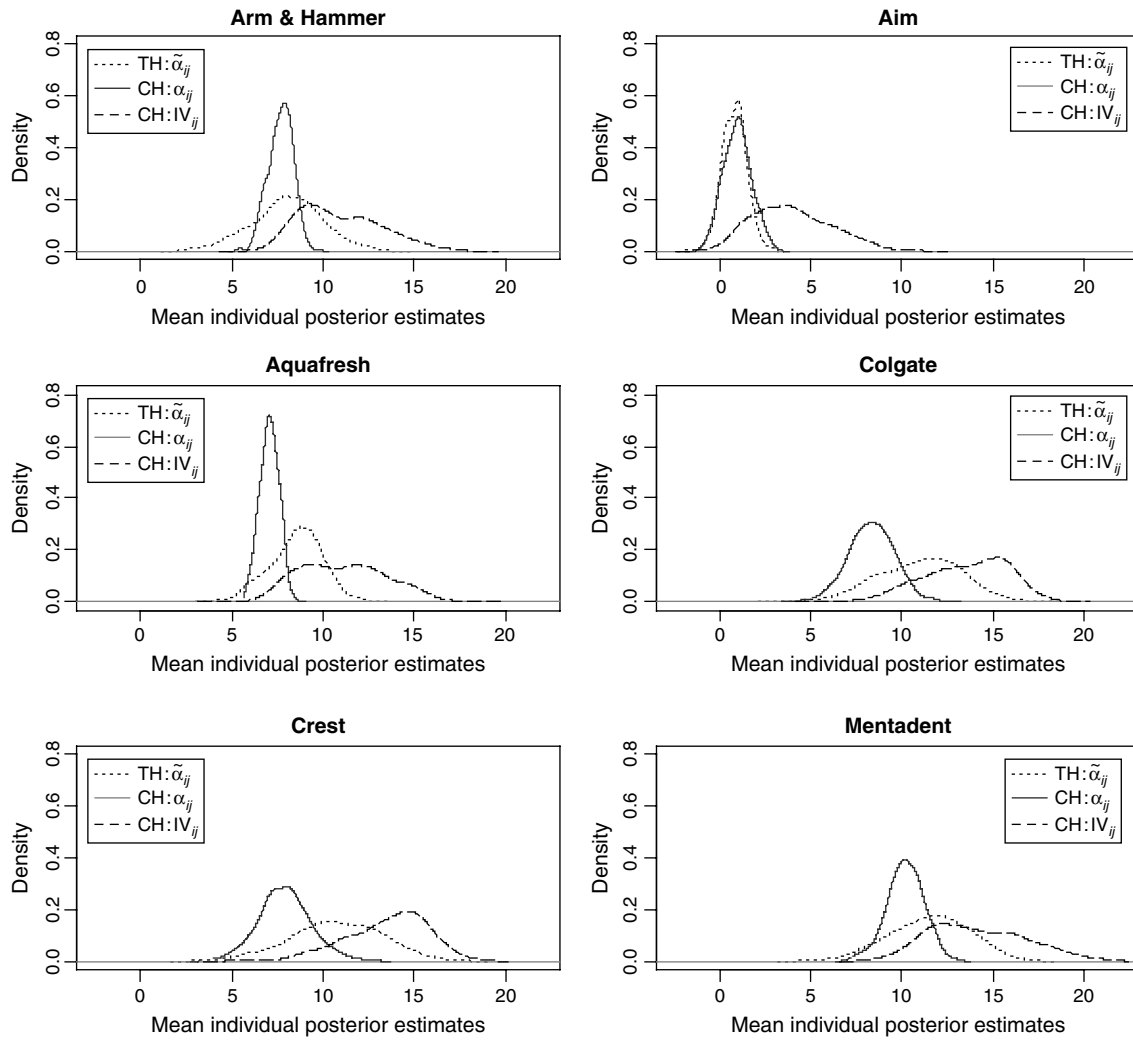
Table 3 **Estimation and Validation Sample Hit Rates[†]**

	Hit rates	
Model	Estimation sample* (%)	Validation sample (%)
Traditional heterogeneity model (TH)	66.85	61.80
Complete heterogeneity model (CH)	73.59	68.11
Complete heterogeneity model (imputation scheme 1)		59.64
Complete heterogeneity model (imputation scheme 2)		60.63

[†]The hit rate is defined as the percentage of choices predicted accurately.
*60% of the sample households belong to the estimation sample. The other 40% belong to the validation sample.

Figure 3   Computed Posterior Density Plots for Brand-Specific Constants and Intrinsic Brand Values

Note. In the legend, for the CH model, $IV_{ij} = \alpha_{ij} + \omega_i \, PREF_{ij}$.
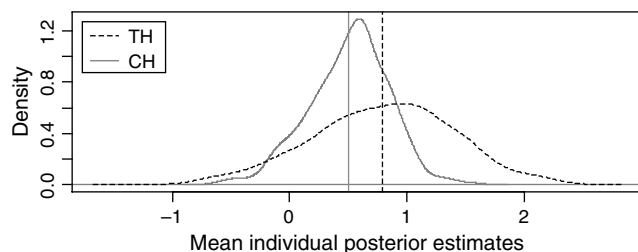
Furthermore, the impact on those households that are correctly targeted is likely overestimated. Similarly, customer relationship programs focused on loyal customers may be mistargeted.

Price Sensitivity

Studies incorporating unobserved heterogeneity emphasize that ignoring the variation in how consumers

Figure 4   Density Plots for the Posterior Loyalty Coefficient $(\beta^{(LOY)})$

Note. The vertical lines represent the mean values of the parameters.

evaluate products may severely bias parameter estimates. Clearly, individual-level measurement of stated brand preferences incorporates such heterogeneity. We suggested earlier that when the researcher has access to "true" preferences the consumer is bound to be less price sensitive, and this should manifest itself in higher intrinsic brand values and/or a lower price coefficient. Indeed, both an increase in the impact of the consumer's intrinsic values IV_{ij} (discussed previously) and a reduced price coefficient are realized.
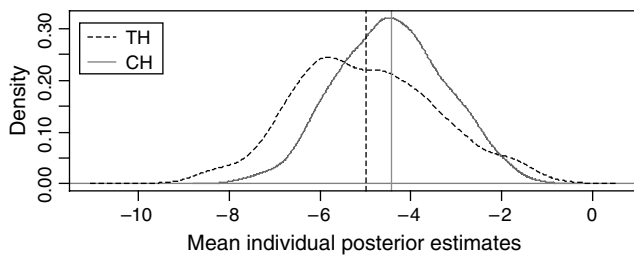
Table 2 reports that the estimated price parameter is *lower* when stated-preference heterogeneity is accounted for. The posterior price coefficient has a mean of -4.9926 and a variance of 2.4817 under the traditional heterogeneity (TH) model. With preference heterogeneity (CH), the mean drops to -4.4307 and the variance plummets to 1.1424. To better examine this issue, Figure 5 plots the individual-specific posterior price coefficients for the TH and CH models.

Figure 5   Density Plots for the Posterior Price Coefficient (θ)

Note. The vertical lines represent the mean values of the parameters.

The rightward shift in this density for the CH model implies that without stated preferences the price effect is exaggerated (negatively biased). A Kolmogorov-Smirnov test supports the hypothesis that the two densities differ and that the density for CH lies to the right of that for TH. Further, the CH density reflects a reduction in the variance of the price effect (a Fligner-Killeen test rejects the hypothesis of equal variances). This is important because the degree of heterogeneity in price sensitivities dictates the potential for price discrimination.

Discussion so far has focused on comparing the posterior parameter estimates of the CH and TH models. Unfortunately, such comparisons across models are problematic due to different implicit scale parameters (Swait and Louviere 1993). However, Hausman-Ruud (1987) tests find that the brand-constant, loyalty, and price coefficient differences discussed above are not explained merely by error variance scaling. Indeed, the improved fit of the CH model implies that the scaling parameter should cause these parameters to increase in both their average magnitudes and dispersions. Our results, however, show that both the loyalty and the price parameter have a *smaller, not larger*, mean and variance. Thus, a clear reduction in the importance to choice of both loyalty and price is indicated. The lower variance in both of these values is also consistent with the better fit provided by the homogeneous parameter OH model relative to the traditional heterogeneous TH model.

Despite this finding, for a more robust comparison of the models' estimated price sensitivities and to ascertain the economic significance of the differences in them, we calculate under each model the estimated own- and cross-price elasticities and carry out a series of counterfactual experiments. These elasticities and experiments also recognize that a consumer's response to price changes is influenced by both intrinsic brand values and the price parameter.

The price elasticity matrices for the TH and CH models are provided in Tables 4 and 5. Own-price elasticities are significantly lower under the CH model (where stated-preference heterogeneity is included).

This is consistent with our expectations and the parameter estimates discussed earlier. Differences in own-price elasticities range from small (Arm & Hammer = 0.33) to substantial (Aim = 1.21). The average difference is large—0.70 (about 16%). Cross-price elasticities, in general, also are smaller in the CH model and as a result, "clout" and "vulnerability" (Kamakura and Russell 1989) are lower under the CH model.[9] In sum, the market is less price competitive when preferences are explicitly accounted for. To ascertain the statistical significance of these differences, a bootstrap procedure was used wherein the elasticity matrix was replicated one hundred times and for each matrix element the percentage of times that the CH elasticity estimate was lower than the TH estimate was identified. All own-price elasticity differences, as well as the differences in clout and vulnerability, are significant at the 1% level.

Counterfactual experiments that examine the revenue generated by list price cuts of 25¢, 50¢, and $1 for each brand illustrate that the differences in the two elasticity matrices are also economically significant. Irrespective of the brand, the TH model tends to be overly optimistic and predicts larger market share and revenue gains than does the CH model. For example, under the TH model, a 25¢ price cut to all consumers for Aquafresh (which has an average-sized own-price elasticity estimate discrepancy of 0.67) increases its market share from 15.4% to 24.2%, while under the CH model the increase is only to 22.6%. Correspondingly, much larger revenue gains occur under the TH model (61%) than under the CH model (53%).[10]

The economic significance of the price elasticity differences is further evoked through a second set of counterfactual price discrimination experiments where for each household we found the price cut (in 5¢ increments) needed to maximize the posterior expected revenue for a particular brand.[11] The results discussed again pertain to Aquafresh and are analogous to those found for the other brands. The CH model requires larger individual-specific price cuts on average than the TH model since the price elasticities are lower. The median price cut needed to induce a switch to Aquafresh under CH is 55¢ while under TH it is 50¢. More importantly, there is little concordance across the two models in the size of the price cut that each particular household received. For example, of the 67 households that got a 60¢ coupon (the

[9] Clout$_j = \sum_{i=1}^{n} \zeta_{ij}$ and vulnerability$_j = \sum_{i=1}^{n} \zeta_{ji}$, where ζ_{ji} is the elasticity of brand i's demand with respect to brand j's price.

[10] These numbers are large because the simulation assumes that the price cut is not just large but also available to all consumers on all purchase occasions.

[11] For a detailed description of a similar experiment, see Rossi et al. (1996).

Table 4 Elasticity Matrix Based on Traditional Heterogeneity (TH) Model[*]

	Arm & Hammer	Aim	Aquafresh	Colgate	Crest	Mentadent	Pepsodent	Vulnerability
Arm & Hammer	−4.6053	0.0797	0.6947	1.7715	1.5726	0.3425	0.0703	**4.5313**
Aim	0.5453	−4.6801	1.7344	2.7517	3.3148	1.0028	0.4696	**9.8186**
Aquafresh	0.3312	0.1132	−3.6103	1.4881	1.6150	0.4388	0.0707	**4.0569**
Colgate	0.3466	0.0792	0.6309	−3.5127	1.7894	0.3957	0.0534	**3.2953**
Crest	0.3163	0.0952	0.6956	1.8207	−3.6583	0.4521	0.0708	**3.4506**
Mentadent	0.1901	0.0801	0.5169	1.1002	1.2532	−4.3661	0.0480	**3.1885**
Pepsodent	0.7331	0.7423	1.6670	2.8996	3.9499	0.9231	−5.3909	**10.9150**
Clout	**2.4627**	**1.1897**	**5.9394**	**11.8317**	**13.4950**	**3.5551**	**0.7827**	

[*] The cells in the matrix should be interpreted as the percentage change in the row brand's demand due to a percentage change in the column brand's price. Clout is measured as the columnwise sum of the cross-price elasticities while vulnerability is the rowwise sum.

highest value) under CH, less than half (28) received a price cut of the same value under TH, with the rest receiving smaller price cuts. Similar discrepancies were found for smaller-sized price cuts. Furthermore, while the average price cut is higher under CH, their standard deviation is actually *lower* (CH = 8¢, TH = 11¢). This likely is a consequence of the lower heterogeneity in the posterior price effect observed with the CH model (see Figure 5).

In sum, the simulation results reveal that any price or coupon (price discrimination) strategy that fails to account for preference heterogeneity is likely to be flawed. In particular, (i) the traditional heterogeneity TH model's overestimated price sensitivities result in suboptimal price and coupon values, and (ii) inaccurate estimation of individual household-specific price sensitivities under the TH model leads to the misidentification of price-sensitive households.

Practical Managerial Implications When Preferences Are Measured for Only a Subsample

A typical brand manager in the United States can avail himself/herself to Nielsen or IRI scanner data on the continuous purchasing behavior of a "large" representative sample (thousands of households). Similarly, some retailers through their loyalty programs have such data on many, if not most, of their

customers, some of whom may do nearly all their purchasing at that retailer. Unfortunately, the individual-level preference survey data used in this paper will at best be collected periodically for a "subsample" of this larger scanner sample. This calls to question the managerial value of our methodology and findings.

The implicit assumption in previous scanner data-based research is that price and promotion decisions based on parameter estimates derived from the large scanner data sample are appropriate for the population as a whole due to the sample's representativeness. Given such representativeness and the sufficient size of our scanner plus survey data subsample, similar populationwide price and promotion insights are appropriate. Correspondingly, at least in our product category, we find for example that the market is less price competitive than a traditional analysis would have revealed. Consequently, managers could, based on our methodology, price and promote their brands in a more profitable manner.

Things are more complicated if the brand manager is interested in targeting price and promotion activity toward a particular segment or individual. Clearly, no such activity is possible concerning consumers in the wider population for whom scanner data are not collected. Hence, our interest lies in how results obtained from our subsample can be applied to a larger scanner database for which preferences are unavailable. Two

Table 5 Elasticity Matrix Based on Complete Heterogeneity (CH) Model[*]

	Arm & Hammer	Aim	Aquafresh	Colgate	Crest	Mentadent	Pepsodent	Vulnerability
Arm & Hammer	−4.2760	0.1138	0.6350	1.5359	1.2774	0.5043	0.0964	**4.1628**
Aim	0.7629	−3.4692	1.5584	1.8556	2.1797	0.5746	0.2913	**7.2225**
Aquafresh	0.3132	0.1085	−2.9474	1.0932	1.2584	0.4085	0.0632	**3.2451**
Colgate	0.3262	0.0592	0.4814	−2.8827	1.4909	0.3164	0.0474	**2.7216**
Crest	0.2754	0.0688	0.5527	1.4904	−3.0086	0.4276	0.0612	**2.8761**
Mentadent	0.2942	0.0506	0.4832	0.8512	1.1623	−3.8719	0.0383	**2.8798**
Pepsodent	1.0115	0.4540	1.4019	2.3382	3.1197	0.6680	−4.4659	**8.9933**
Clout	**2.9833**	**0.8549**	**5.1127**	**9.1645**	**10.4884**	**2.8995**	**0.5978**	

[*] The cells in the matrix should be interpreted as the percentage change in the row brand's demand due to a percentage change in the column brand's price. Clout is measured as the columnwise sum of the cross-price elasticities while vulnerability is the rowwise sum.

questions are of interest: (i) How well does the CH model estimated on our subsample predict individual choice behavior in another holdout sample where preferences are unknown? (ii) Does the CH model provide better general and targeted price and promotion decisions for such a holdout sample? The latter issue is clearly of greater relevance to managers wishing to make proactive marketing mix decisions.

With respect to the prediction of individual-level choices in such a holdout sample, careful comparisons are needed. By definition, any out-of-sample prediction based on TH model parameters will outperform that derived using CH model parameters if the latter does not include individual-level preferences. In essence, ignoring preferences is akin to forcing the researcher to set preferences ($PREF_{ij}$) to zero. Under such a scenario, while both predictions are made based on the same set of variables, the TH model does better because its parameters were estimated based solely on the variables available in the holdout sample. However, if fairly accurate proxies for individual preferences are available, we can take advantage of the more managerially relevant parameter estimates of the CH model (e.g., its more accurate price sensitivity estimates). In fact, simple imputation techniques based on the means and distributions of the subsample preferences can generate reasonable proxies for this preference information. The bottom of Table 4 presents validation sample prediction results using two imputation schemes.

In imputation scheme CH-1 the "missing" preferences in the holdout sample are proxied for by their estimation sample means (i.e., the average preferences for each brand are simply "plugged" into each holdout consumer's utility function). We then use the scanner data for the holdout sample along with the estimated CH model parameters to predict choices in the holdout sample. Imputation scheme CH-2 uses a Monte Carlo procedure to approximate the distribution of the "missing" brand preferences. In both cases—despite the absence of actual observed preference information—the predictive power of the CH-1 and CH-2 models is very close to that of the TH model (i.e., within 1% to 2%).[12]

To illustrate that imputed preference values for the holdout sample also provide improved general and targeted price and promotion decisions designed specifically for that holdout sample (i.e., that are closer to those based on the CH model with actual preferences than those made using the TH framework), we conduct simulations using the logic of

imputation scheme CH-2. Even though actual preferences are unavailable in the holdout sample, the *empirical distribution* of preferences from the estimation sample is available to the manager.[13] Using this empirical distribution we can integrate out preferences along with other unobservables (heterogeneity) from any quantity of interest. Hence, denoting individual consumer preferences ζ_i and other unobserved factors by $\mathbf{\Lambda}_i$, the profit a firm can generate from a given consumer i in the holdout sample is

$$\widehat{\Pi}_{it} = \int \left[(p_{jt} - c_j)\pi_{ijt}(\mathbf{p}_t, \mathbf{O}_t, \zeta_i, \mathbf{\Lambda}_i) \right] dF(\zeta, \mathbf{\Lambda}),$$

where $\pi_{ijt}(\mathbf{p}_t, \mathbf{O}_t, \zeta_{ii}, \mathbf{\Lambda}_i)$ is the probability that person i purchases brand j at time t. $\mathbf{p}_t$ represents the vector of prices and $\mathbf{O}_t$ the other observable factors at time t, while c_j is the product cost. To evaluate this integral and thereby carry out various counterfactual experiments, a Monte Carlo approach is used to generate a large number of draws (100) from the joint empirical distribution of the preferences available in the estimation sample and average the relevant objective function.[14]

Using this imputation framework and the list price cut simulation structure described earlier, counterfactual experiments for the holdout subsample (without preference data) again looked at changes in share and revenue generated by list price cuts of 25¢, 50¢, and $1 for each brand. Results are similar in nature across brands and price cut sizes. For example, a 25¢ price cut by Aquafresh increases the holdout market share from 15.5% to 24.8% under the TH model. Under the CH model using preferences imputed from their observed empirical distribution (CH-2), an increase to only 22.7% is predicted while the CH model using the holdout sample's *actual* preferences predicts a new market share of 23.1%. Correspondingly, the projected revenue gain under the TH model (63%) also differs more from that of the CH model (55%) than does that of the CH-2 model (57%). Clearly, using imputed preference values and then integrating them out in the holdout sample (CH-2) realizes estimated price sensitivities that are closer to what is likely true (CH) than does ignoring this preference information (TH).

Price discrimination counterfactual experiments on the holdout sample also show that targeted pricing is more accurate (closer to that implied by the CH model) under the CH-2 model than under the TH model. As before, for each holdout household we found the price cut that maximized the posterior expected revenue for a particular brand. The

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[12] More complex imputation schemes with better predictive power than the TH model are possible. For example, Bayes' rule allows improved estimates of the individual-level preferences for the holdout sample by conditioning on observed choices and marketing mix data.

[13] This implicitly assumes that the holdout and estimation samples are drawn from the same population.

[14] This approach clearly is second best in that we only use the distribution of preferences and not actual preferences.

price discrimination results presented again pertain to Aquafresh and are analogous to those found for the other brands. The median individual-specific price cut is 55¢ (with a standard deviation of 9¢) under the CH model while under TH model it is 50¢ (with a standard deviation of 11¢). The CH-2 approach again outperforms the TH model in that its median price cut is 55¢ with a standard deviation of 10¢. We also find that the distribution of price cuts under CH-2 is more similar to that of the CH model than is the distribution for the TH model. In addition, there is a lower degree of consumer misclassification under CH-2 than under TH.

In sum, from a practical perspective preference survey data need only be collected from a subset of the scanner panel participants in order to foster significant managerial benefits. Our simulations strongly support the notion that for a holdout sample of consumers for whom preference data have not been collected, imputed preference values along with CH model parameters (referred to above as CH-2) allow for both general and targeted price and promotion decisions that are closer to those implied by the CH model (with actual preference data) than those based on the TH model. Assuming that the CH model better reflects actual behavior and, hence, defines managerial decisions that are more nearly optimal, we conclude that even if preference data for the holdout sample must be imputed, managers are likely to make better decisions than they would using the TH model.

Summary

This paper developed a model of consumer choice behavior that integrates stated consumer preference heterogeneity into a scanner-based brand-choice framework. We find that including survey-based individual-specific preference measures allows us to much better account for cross-sectional variation across households and, consequently, results in more precise estimates of how strongly time-varying marketing variables impact choice. Moreover, model fit and prediction are improved more through incorporating this "observed" heterogeneity than through incorporating "unobserved" parameter heterogeneity. Further, measuring individual-specific stated preferences and incorporating this measure into heterogeneous scanner models greatly outperforms trying to approximate these idiosyncratic differences by a specified stochastic formulation. This finding has its roots in the fact that the underlying individual-level preferences over the brands and their heterogeneity across people are not nearly as "well behaved" as previously assumed.

From a managerial perspective, our results imply that standard scanner data models, even those incorporating both unobserved and observed demographic parameter heterogeneity, underestimate the importance of consumers' brand preferences and provide overstated price elasticity estimates. The price parameter is reduced and the impact of intrinsic brand value is increased when brand-preference heterogeneity is explicitly modeled and measured. This happens because the "real" preference-based consumer is more reluctant than the "average" consumer to switch from his preferred brand. The implication is that a manager relying on standard scanner model results may price their brand suboptimally. The improved estimation of price elasticities that results when consumer preferences are modeled should allow managers to more accurately optimize the prices of their brands as well as price discriminate.

The importance of brand loyalty is also overstated in standard models. This occurs because the individual-specific nature of the past purchase-based loyalty measure erroneously picks up brand preferences as well as state dependence. In our specification this bias is reduced because preference heterogeneity is explicitly modeled. As a result, loyalty retains a significant although reduced impact on choice. For a manager, this means that periodic price promotions remain optimal since past purchases influence future purchases (Freimer and Horsky 2006), but it also means that this future purchase incentive is less strong than is implied by standard scanner models.

Key targeting implications are also identified. Ignoring stated preferences in brand-choice models mischaracterizes the heterogeneity in the population. First, the heterogeneity in both price and loyalty sensitivity is exaggerated. Second, *different* households are found to lie at the extremes of these heterogeneity distributions. As we have shown, these findings have important implications for the efficient targeting of promotion and price discrimination strategies.

In conclusion, more accurate managerial implications due to improved understanding of choice behavior result if joint survey and scanner data are used to estimate the brand-choice model described in this paper. Furthermore, such combined data need be collected only from a subsample of the scanner panel members. For populationwide price and promotion insights the representability of such a subsample ensures the generalizability of its results. For individual-level targeting insights concerning scanner panel consumers for whom preferences are unavailable, the parameter estimates derived from the joint data subsample and a simple scheme to impute the preferences in the "holdout" panel provide superior price and promotion implications. It is thus evident that the more complex and expensive data collection process needed to acquire the joint scanner and survey data appears well worth its cost.

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