Observed and Unobserved Preference Heterogeneity
In Brand Choice Models

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ABSTRACT

In deciding what brand to buy consumers trade off between how valuable each brand is to them and its price. Scanner data based brand choice models that evaluate this trade off and allow for unobserved heterogeneity are a very popular topic. We extend this line of research by explicitly incorporating brand preferences rather than just utilizing brand specific constants and past purchase behavior to proxy for them. We illustrate our model using a unique dataset that combines survey and scanner data collected from the same individuals. The addition of individual specific brand preference information to a standard scanner choice model that incorporates brand specific constants, loyalty, promotion and price significantly improves how well choices are explained and predicted. Moreover, this “observed” heterogeneity via inclusion of individual specific brand preferences better explains choice than does “unobserved” heterogeneity in the standard scanner model parameters. This is largely due to the inability of the researcher to specify unobserved heterogeneity distributions that fully capture the heterogeneity underlying consumer preferences. We find that a model which does not include the individual level preference information overestimates both brand loyalty and price sensitivities. The brand loyalty coefficient is overestimated because models without preference information confound state dependence, heterogeneity and preference effects. Price sensitivities are reduced in the more complete model because the “real” preference based consumer is less ready to switch from his most preferred brand than is the “average” preference based consumer implicitly used in standard models. Furthermore, we find that, the lack of cross-sectional survey information on the differences in preferences across households causes the standard models to overestimate the heterogeneity in price and loyalty sensitivities. This also results in these models commonly misidentifying both high and low price and loyalty sensitive consumers. Our more accurate loyalty and price sensitivity estimates should help managers set prices and target promotions better.

Key words: Discrete Choice, Heterogeneity, Scanner Data
INTRODUCTION

Managerial decisions concerning brand strategy and tactics are typically based on an understanding of how consumer brand choice behavior is influenced by marketing factors, such as price, which are controlled by the firm. Since the pioneering work of Guadagni and Little (1983) brand choice models calibrated on scanner data have helped increase our understanding of the impact of these controllable factors on choice in frequently purchased product categories. It also has been recognized that consumers are heterogeneous in their response to these factors, and that accounting for such heterogeneity is critical to uncovering consistent, unbiased and realistic effects. Data limitations, however, have precluded individual consumer level parameter estimation and, hence, researchers have relied on parametric assumptions to attack this issue. Typically, heterogeneity is incorporated by overlaying a mixing distribution on the parameters of interest. The two most popular approaches use a multivariate normal distribution (e.g. Gonul and Srinivasan 1993; Allenby and Rossi 1999) or a discrete point mass density\(^1\) (e.g. Kamakura and Russell 1989; Chintagunta and Gupta 1994). In a recent paper Andrews, Ainslie and Currim (2002) show that incorporating heterogeneity in either form improves model fit and results in better parameter recovery.

Another major reason for including heterogeneity, particularly in the brand specific constants, is to acknowledge that differences exist in the underlying preferences consumers have for the alternative brands. By allowing for a stochastic implementation of heterogeneity in these constants the researcher induces a particular pattern of differences in brand preferences across consumers. Thus, implicitly, researchers rely on an accurate mapping of the true preference

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\(^1\) This class of models is also known as Latent Class or Finite Mixture models.
heterogeneity to this stochastic counterpart. However, if this mapping is inadequate, then clearly
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?
The availability of such “observed” preference heterogeneity would allow us to better understand
the nature of consumer heterogeneity. This observed distribution of heterogeneity, if informative,
should also explain the purchase data better, uncover possible biases in parameter estimates and,
consequently, help managers make better decisions. This paper addresses these very issues.
Using a unique dataset that contains both scanner panel data and survey based brand preferences
from the same set of individuals we construct and implement discrete choice models that explore
and contrast the benefits of observed and unobserved heterogeneity specifications.

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

The paper proceeds as follows. We start with a brief review of the literature on consumer utility and brand choice which leads to a set of models that we propose to evaluate empirically. Next, we discuss what impact the inclusion of observed preferences may have on the choice model. Our dataset is then described and the various constructs used in the analysis operationalized. Then, we examine our models utilizing these data and compare their fit, predictive ability and parameter estimates. Utilizing these empirical results, our key findings and their managerial implications are discussed. 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. Following, Rosen (1974), and assuming additive separability, the utility of brand $j$ to consumer $i$ at time $t$ is depicted as a benefit/cost tradeoff, 

$$U_{ijt} = V_{ijt} - f_p (p_{ijt})$$

(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 $t$. 


The total brand value, $V_{jt}$, clearly depends on the characteristics of the brand and its marketing environment, as well as the consumer’s perceptions of and reactions to them. As such, the consumer’s perceptions of the attribute content of each brand and the relative importances of these attributes are central to the total brand value$^2$ (Lancaster 1966; Fishbein 1967). They lead to an “intrinsic brand value” $IV_{ij}$, which is updated over time as the consumer learns through brand consumption experiences or is influenced by state dependence (Massey, Montgomery and Morrison 1970). Moreover, total brand value also is impacted by the brand’s promotion activity which influences awareness and so forth.

The key issue in this paper concerns how individual specific intrinsic brand value $IV_{ij}$ previously has been measured and whether this can be improved upon. Improved specification and measurement of brand value ($IV_{ij}$, and, hence, also $V_{jt}$) 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 actual 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

$$U_{ijt} = \alpha_{ij} + \beta_i'X_{ijt} - \theta_jp_{jt} + \varepsilon_{ijt}.$$  

(2)

In the above, the intrinsic brand value ($IV_{ij}$) that consumer $i$ places on brand $j$ is proxied for by brand specific constants $\alpha_{ij}$. The vector $X_{ijt}$ 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 $V_{ij} = \alpha_{ij} + \beta_i'X_{ij}$. $p_{jt}$ is the price paid by

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$^2$ Brand equity unrelated to the attributes may be seen as an additional “attribute”.

consumer $i$ for brand $j$ at time $t$. $e_{ijt}$ is a stochastic component that is usually assumed to be distributed i.i.d. Gumbel. It then 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 $\tilde{\alpha}_j, \beta_i$ and $\theta_i$ is used to represent the “unobserved” heterogeneity across individuals $i$ in these parameters. In addition we also allow the individual specific parameters to be functions of demographics. Details of this approach are made clear below.

**Brand Choice Model with Complete Heterogeneity (CH)**

The model we propose in this paper (CH) extends the traditional heterogeneity framework by including a stated preference measure (i.e., “observed” heterogeneity) into the utility function. In other words, we define intrinsic brand value as $IV_j = \alpha_j + \omega_iPREF_{ij}$ where $PREF_{ij}$ denotes the preference of consumer $i$ for brand $j$. This results in

$$U_{ijt} = \alpha_j + \omega_iPREF_{ij} + \beta_i'x_{ijt} - \theta_iP_{ijt} + e_{ijt}. \quad (3)$$

In addition to allowing for unobserved heterogeneity we also let the parameters in both the CH and TH models be functions of a second type of “observed” heterogeneity - household demographics ($z_i$). That is, the model parameters are defined as

$$\begin{bmatrix} \alpha_{ij} \\ \omega_i \\ \beta_i \\ \theta_i \end{bmatrix} = \begin{bmatrix} \alpha_j \\ \omega \\ \beta \\ \theta \end{bmatrix} + \begin{bmatrix} \delta^{(\omega)} \\ \delta^{(\alpha)} \\ \delta^{(\beta)} \\ \delta^{(\theta)} \end{bmatrix} z_i + \begin{bmatrix} \eta_{ij}^{(\omega)} \\ \eta_i^{(\alpha)} \\ \eta_i^{(\beta)} \\ \eta_i^{(\theta)} \end{bmatrix}, \quad (4)$$

where the $\eta$ are random deviates that are jointly distributed multivariate normal with mean zero and variance covariance matrix $\Sigma_\eta$. Hence, the Traditional Heterogeneity (TH) model is obtained by ignoring the effect of stated preference information but allowing for unobserved **and**
observed demographics heterogeneity in the parameters. In sum, $TH$ is a restricted version of $CH$ with $\omega_i = 0$ for all $i$.

The $CH$ specification outlined by equations (3) and (4) accounts for multiple sources of heterogeneity including: (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 components. Thus, the model not only allows consumers to react differently to marketing stimuli but also to have different preferences and have these preferences impact choices idiosyncratically.

Comparison of these two 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 the $TH$ model recover the averages of these 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 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., the $\eta$ in equation (4) are set to zero).

**WHY INCLUDE OBSERVED PREFERENCE HETEROGENEITY?**

The rationale for including survey based individual specific preferences in brand choice models stems from the fact that they are able to more accurately reflect the cross-sectional
differences that exist across households. In such, their inclusion allows us to more accurately exploit the “panel” nature of scanner data and permits better measurement of the effects of time varying variables such as price and promotion. As a result, we expect to obtain models that fit better and afford cleaner, more precise estimates of effects that are important to managers and researchers. In what follows we delineate the impact that the inclusion of preferences might have on four key areas.

**Fit and Prediction**

The integration of observed preference heterogeneity into scanner based brand choice models obviously allows examination of how such information impacts estimation results. In particular, if the informational content of this variable is significant, we should see an improvement in model fit and predictive ability. More importantly, from a managerial viewpoint, this integration may alter our existing knowledge of how the brand specific constants, brand loyalty, and price influence choice.

**Brand Specific Constants**

The extant literature posits that the brand specific constants ($\alpha$) included in the traditional heterogeneity utility specification (2) represent the intrinsic values of the brands in question. Clearly heterogeneity in preferences is an individual specific manifestation of this same construct. An examination of equations (2) and (3) highlights the fact that heterogeneity in the brand specific constants is motivated by differences across people in their brand preferences. This heterogeneity has its roots in the differences that exist across people in how they perceive the attribute levels of each particular brand and in the relative importances assigned to the attributes. This multi-attribute perspective for the brand specific constants provides the impetus for the market structure “Choice Map” literature (e.g., Kamakura and Russell 1993; Chintagunta
1994; Elrod and Keane 1995). If this interpretation of the brand constants is true, we should expect the variation in the newly included observed preference measure to cause a reduction in both the magnitude of the constants as well as their variances.

**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 combined heterogeneity CH model incorporates stated preferences as well as parameter heterogeneity, the relevance of the brand loyalty variable should be reduced, as it now only measures 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**

The impact of prices on choice is governed by the difference in preference between a consumer’s most and second most (or lower) preferred brands. In other words, 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. This interpretation is not new and is well accepted in the economics and marketing literatures (e.g., Nevo 2000).

Traditional scanner based brand choice models rely on characterizing the intrinsic brand values or preferences of a consumer using his/her string of observed choices and the choices of other consumers (i.e., market share). That is, in essence, the estimated individual specific brand specific constants (\( \tilde{\alpha}_g \) in equation (2)), can be seen as shrinkage estimators (with shrinkage towards the preferences of the “average” consumer). As such, these estimators necessarily
underestimate the true magnitude and dispersion of preferences in the population. In contrast, when stated preferences are known, there is less reliance on the “average” consumer’s preferences. The corresponding reduced price sensitivity (i.e., a greater price cut is required to cause switching) may manifest itself in a reduced price coefficient and/or in an increase in the joint impact of the constructs which measure consumer preferences (intrinsic brand values) – the brand specific constants and observed preferences. The net result of these effects is a lower overall impact of price changes on consumer choice.

This effect is noted although not articulated in the literature (e.g., Fader 1993; Erdem 1996; Erdem and Keane 1996). In these papers, when a more flexible specification is adopted on the intrinsic brand values, the estimated price effect is lowered. While these authors offer a varied set of explanations we believe that our argument offers a simple explanation that is consistent with economic theory.

The inclusion of observed preferences into the utility function should also have an impact on the degree of heterogeneity in the price coefficient. Including preference information allows the model to better account for cross-sectional differences and thus facilitates a cleaner estimate of the influence that inter-temporal 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 estimated heterogeneity. In the CH model, on the other hand this problem is mitigated and, consequently, the heterogeneity in the price effect will be lower. 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 will also be reduced.
DATA AND ESTIMATION

Data
A unique dataset 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 US who made at least four toothpaste purchases during the year analyzed. Inquiries concerning the seven major brands in the toothpaste category were made. These seven brands - Aim, Arm & Hammer, Aqua Fresh, Colgate, Crest, Mentadent and Pepsodent - totaled 86% of U.S. category sales at the time. Our measure of observed preference is a 1 (low) to 7 (high) rating of how much each respondent liked each brand.

The 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 average 9.11 over this period (5560 choices). The \( x_{ijt} \) vector utilized consists of two variables \( \{ LOY_{ijt}, DISP_{ijt} \} \). The display variable \( DISP_{ijt} \) as measured by IRI is a scaled index (between 0 and 1) 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 which is equal to one if brand \( j \) was purchased at time \( t-1 \). Two variables also are used for the observed heterogeneity components \( z_i \) pertaining to demographics. These are family size \(FSIZE_i\) and household income \( HHINC_i\). In other words, \( z_i = \{FSIZE_i, HHINC_i\} \). As done in most papers, we utilize shelf price
inclusive of any temporary price reduction to measure price $p_{it}$ 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. While descriptive statistics can never fully describe a market, the information does provide some insights into its structure. The two large market share brands - Colgate and Crest – are, on average, also rated the highest on the preference measure. Furthermore, they are among the higher but not the highest priced brands. Crest, the market leader when compared to Colgate, is higher on the liking measure and priced lower but is put on display much less frequently.

The two smallest market share brands - Aim and Pepsodent - also have, on average, low liking ratings and prices. The price variability of Aim, as measured by the coefficient of variation, is higher than the other brands in the sample. The share of the third largest brand – Aquafresh - is consistent with its preference rating and price. Mentadent, which rates fourth in share, has the highest price and appears too highly priced given the way the average consumer rates it on liking. However, the standard deviation of its liking ratings is the highest of all brands. Arm and Hammer, the fifth largest share brand and the second highest priced, is similar to Mentadent in that its liking standard deviation also is high. This heterogeneity indicates that, to a greater extent than in other brands, there exists a segment of consumers who value these latter two brands very highly and constitute their core consumers.

The discussion in the previous paragraphs suggests that there is a reasonable amount of preference heterogeneity in the data. Given the uniqueness of the dataset and the focus of this paper we feel this aspect warrants further elaboration. Figures 1 and 2 highlight various facets of preference heterogeneity in the consumer base. The histograms depicted in Figure 1 show that different brands have very different distributions when it comes to preference. For example,
Colgate and Crest have distributions that are skewed towards the higher values while preferences for Mentadent are spread rather evenly. While Figure 1 shows strong preference differences across consumers for a given brand, 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 member #13 or #16). What should be clear from the two figures is that approximating the true distribution of preferences using uninformative parametric (or non-parametric) distributions is a rather difficult task.

**Econometric Implementation**

We adopt a Bayesian MCMC (Markov Chain Monte Carlo) approach to implement the models presented in this research. The MCMC procedure relies on an iterative scheme that draws from the joint posterior of the parameters of interest. Since the estimation methods used are well documented in the literature we do not provide details.³

**DISCUSSION OF RESULTS**

This section concentrates on the four key areas of interest raised earlier concerning how the modeling of observed preference heterogeneity impacts: (i) fit and prediction; (ii) the brand specific constants; (iii) the relevance of brand loyalty; and (iv) price sensitivity. Discussion focuses on a comparison of the models depicting complete heterogeneity \((CH)\), observed heterogeneity in preferences, parameter heterogeneity through demographic and unobserved heterogeneity), and traditional heterogeneity \((TH)\), without observed heterogeneity in preferences). Tables 2 and 3 report the estimation results for these models.

³ For details on similar models see Allenby and Rossi (1999) and Wedel, et al. (1999). Specific details of the MCMC approach used in this paper are available from the authors.
Fit and Prediction

The fit results in Tables 2 and 3 clearly show that a complete specification of heterogeneity (\(CH\)) outperforms the traditional heterogeneity (\(TH\)) model. Using the harmonic mean approach proposed by Newton and Raftery (1994) we compute the log marginal likelihoods for the two models (\(CH = -3149.1\), \(TH = -3304.6\)). While the superiority of the \(CH\) model is not surprising, the magnitude of superiority is. Using the comparison criteria proposed by Kass and Raftery (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 all parameters in 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 also is important.

The importance of stated preferences in describing choice is further 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 \(-3218.7\)) than does the \(TH\) model. The inclusion of stated preferences into a homogeneous brand choice model allows different consumers to have different preferences but does not allow the impact of any variables to be heterogeneous. On the other hand, the \(TH\) model does not contain individual level preference information but does allow for individual level differences 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 might have on utility and 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 incorporating observed preferences as a source of heterogeneity does a better job of explaining choices than simply allowing a degree of flexibility in how observed variables impact choice. In other words, the “average” preferences implicitly used by the TH model simply do not accurately reflect the true individual specific preferences.

The strong superiority in fit of the CH model over the TH model carries over into out-of-sample prediction. This was evaluated by splitting the data into estimation (60% of households) and validation samples (40% of households) and re-estimating the models on the estimation sample. We then used these parameter estimates to predict the choices of both samples. Prediction results are given in Table 4. The CH model has a significantly higher hit rate (percentage of choices predicted accurately) in both the estimation and validation samples than does the TH model (73.59% vs. 66.85% for the estimation sample and 68.11% vs. 61.8% for the validation sample). Furthermore, even if preference data is unavailable for the validation sample, simple imputation techniques that generate proxies for this information based on the estimation sample provide nearly equal predictive ability to the TH model. To address this issue Table 4 presents validation sample prediction results using two very simple imputation schemes. Imputation scheme #1 replaces the actual preference measures for each brand with the average from the estimation sample (which given that our data shows strong preference heterogeneity is not very informative). Scheme #2 uses a bit more sophisticated method to integrate out the missing brand preferences. This was done using a Monte-Carlo procedure which entailed drawing from the empirical distribution of preferences in the estimation sample and averaging out the choice probabilities in the validation sample. In both cases, even in the absence of actual observed preference information the predictive power of the CH model is within 2% of the TH

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4 Note that the estimation and validation samples have no households in common.
model. We conjecture that better imputation methods (e.g., Multiple Imputation and Data Fusion) would improve out of sample predictive ability further.

If preference information is not available out of sample the manager is faced with the following options: (i) collect such preference information; (ii) use preferences in estimation and some imputation method for out of sample prediction; or (iii) ignore the stated preferences altogether (i.e., in both estimation and prediction). In the discussion that follows we show that the cost of ignoring stated preferences can be high since doing so can severely distort decisions pertaining to pricing and targeting. In addition, the cost of collecting preference information is relatively small and provides significantly better prediction.

**Brand Specific Constants and Intrinsic Brand Value**

A commonly held belief in the marketing research community is that the brand specific constants of the traditional heterogeneity \( TH \) model (i.e., in equation (2) \( IV_i = \tilde{\alpha}_i \)) reflect the intrinsic value of their respective brands. Our results show that this is indeed the case. The incorporation of stated preference data in the \( CH \) model has a two-fold impact on the constants. First, the magnitudes of the brand constants are reduced (see Tables 2 and 3). This is expected since the brand constants no longer fully account for the intrinsic brand values of the consumer (i.e., \( IV_i = \alpha_i + \omega_iPREF_i \) under the \( CH \) model). More significant is the finding that the variances of these constants fall dramatically. Figure 3 exhibits these effects graphically. These graphs depict the distribution of the individual level posterior estimates for the brand constants under both the \( TH \) (\( \tilde{\alpha}_i \)) and \( CH \) (\( \alpha_i \)) models. Visual examination shows that the densities are tighter and shifted to the left (i.e., smaller) when stated preference heterogeneity is added. The only exception is Aim which moves little. To verify that these differences in the posterior densities are
statistically significant both a two sample Kolmogorov-Smirnov\textsuperscript{5} and a Fligner-Killeen\textsuperscript{6} test were 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 included in Figure 3 is the posterior distribution of intrinsic brand values $(IV_{ij} = \alpha_{ij} + \omega_iPREF_{ij})$ in the $CH$ model. This connotes a fairer comparison with the brand constants (intrinsic brand values $\tilde{\alpha}_{ij}$) of the $TH$ model. The distributions of these $IV$s are clearly to the right of the $TH$ model brand constant posterior distributions indicating that larger intrinsic brand values are recovered on average under the $CH$ model. Indeed, once again, Kolmogrov-Smirnov and Fligner-Killeen tests find that the distribution differences are statistically significant at the 5\% level. This implies that the intrinsic brand values of consumers are more important to choice than the unobserved heterogeneity based estimates would lead you to believe, This also is consistent with our earlier discussion of how unobserved heterogeneity based estimators of brand value are shrunk towards the average.

A further comparison of the distributions of the $IV$ values for the $CH$ model and the brand specific constants of the $TH$ model demonstrates the inability of the $TH$ model’s imposed stochastic distribution to accurately recover the intrinsic brand value distributions. Aside from the fact that all of the brands have much more dispersed intrinsic value ($IV$) densities, an important revelation depicted in Figure 3 is that each brand has a set of consumers that exhibit relatively high valuations for it. In brands such as Arm and Hammer, AquaFresh and Mentadent

\textsuperscript{5} The Kolmogorov-Smirnov test is a non-parametric test that compares the empirical CDFs generated by two independent samples. The null hypothesis is that the two samples arise from the same density. For more details see DeGroot (1991).

\textsuperscript{6} The Fligner-Killeen test (Fligner and Killeen 1976) is a distribution free test to compare the scales (variances) for two densities. The null hypothesis is that the scales are equal.
this is especially pronounced and manifests itself as the bimodality in the IV densities obtained under the CH framework. This finding has strong implications for pricing strategy and is discussed shortly.

**Brand Loyalty**

Figure 4 depicts the impact that stated preference heterogeneity has on the brand loyalty coefficients (i.e., the graph plots the posterior means of $\beta_i^{(LOY)} = \beta^{(LOY)} + \delta^{(LOY)} z_i$). 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 larger mean and variance under the TH model (also see Tables 2 and 3). The fact that loyalty remains significant is important and is in line with Keane’s (1997) finding that even with very rich specifications for heterogeneity strong loyalty effects remain. There are also differences in how household characteristics affect loyalty. The $\delta^{(LOY)}$ parameters under the TH model suggest that higher income households are less likely to be loyal while the CH model results imply demographics do not play a role.

Surprisingly, we also find that the two models identify different households to be loyal or variety seeking (i.e., have a negative $\beta_i^{(LOY)}$). We ranked households using the mean of their posterior loyalty coefficient and examined the concordance in the top (loyals) and bottom (variety seekers) 10% of the households. In other words we “tagged” the 10% most and least loyal consumers based on the results of each model. The concordance between the two is only 40%. That is, in 60% of the cases a consumer classified as extremely loyal (or variety seeking) by one model was not considered so by the other model. This suggests that the models differ substantially in who is deemed a loyal (or variety seeking) consumer.
The managerial import of this segmentation finding as well as the \textit{TH} model’s smaller loyalty parameter in general is obvious. If, for example, a supermarket is giving away free samples or coupons to households identified using the traditional \textit{TH} model with the hope of inducing trial and subsequent repurchase it may be targeting the wrong households and the impact on those households that are correctly targeted may likely be overestimated. Similarly, customer relationship programs focused on loyal customers may be mistargeted.

**Price Sensitivity**

Studies incorporating unobserved heterogeneity often emphasize that without this added complexity significantly different price parameter estimates result. In other words, ignoring heterogeneity in how consumers evaluate products may severely bias parameter estimates. Since a stated measure of brand preference likely incorporates such unmeasured tradeoffs, including it in the utility specification gives us an opportunity to uncover such a bias. We suggested earlier that when the researcher has access to “true” preferences the consumer is bound to be less price-sensitive. This manifests itself in either a reduced price coefficient and/or in an increase in the joint impact of the constructs which measure the consumer’s intrinsic brand values $IV_{ij}$ (i.e., the brand constants and the observed preferences). In other words, price has a lower impact on choice when the intrinsic brand value increases or the price coefficient decreases.

We have already shown that the intrinsic brand values of the \textit{CH} model are higher and more dispersed than the brand specific constants of the \textit{TH} model (see Figure 3). In addition, our results suggest that the estimated price parameter also is lower when stated preference heterogeneity is accounted for. In particular, Table 2 shows that the mean of the posterior price coefficient ($\hat{\theta}_i = \theta + \delta^{(i)} z_i$) has a mean of -4.9926 and a variance of 2.4817 when only traditional heterogeneity is modeled (\textit{TH}). With preference heterogeneity (\textit{CH}) the mean drops to -4.4307.
and the variance drops considerably to 1.1424 (see Table 3). To better examine the impact of observed preference heterogeneity we plot the computed individual specific posterior price coefficients for the TH and CH models in Figure 5. The rightward shift in the kernel density for the CH model implies that without stated preference measures the price effect is negatively biased (i.e., it is exaggerated). Kolmogorov-Smirnov tests support the hypothesis that the densities are different and that the CH based density lies to the right of the TH based density. Further, the CH model also has a tighter price density which 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 is a measure of the potential for price discrimination. The CH model results also show that larger families tend to be more price-sensitive while higher income households are less so. Alternatively, the TH model fails to provide the income finding.

Our discussion thus far has focused on comparing the posterior parameter estimates of the CH and TH models. Unfortunately, such comparisons across models may be problematic due to different implicit scale parameters (Swait and Louviere 1993). However, Hausmann-Ruud (1987) tests find that the differences discussed above are not explained away merely by scaling. Indeed, the improved fit of the CH model implies that the scaling parameter should cause the estimated parameter values to increase in magnitude. Our results, however, show that both the brand specific constants and the price parameter are smaller not larger in magnitude.

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 the estimated own and cross price elasticities of each model and utilize a series of counterfactual
experiments. These elasticities and experiments also recognize that both the intrinsic brand values and the price parameter impact price sensitivity.

The price elasticity matrices for the TH and CH models are provided in Tables 5 and 6. We find that own price elasticities are significantly lower in the CH model (where stated preference heterogeneity is included). This is consistent with our expectations and the parameter estimates discussed earlier. What is also interesting is that the difference in own price elasticities ranges from fairly small (Arm & Hammer = .33) to quite substantial (Aim = 1.21). The average difference in own price elasticities between the two models is substantial – 0.70 or about 16%.

The cross price elasticities, in most cases, also are smaller in the CH model and as a result, Clout and Vulnerability estimates (Kamakura and Russell 1989) obtained under the CH model are lower. 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 (using new samples from the posterior) 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.

The differences in the two matrices also are economically significant. We implemented a number of counterfactual experiments that examined changes in revenue generated by price cuts of 25¢, 50¢ and $1 for each brand to illustrate this. These simulations show that irrespective of the brand the TH model tends to be excessively optimistic and predicts larger gains in market

7 Following Kamakura and Russell (1989), Clout = \( \sum_{x} \zeta_x \) and Vulnerability = \( \sum_{x} \zeta_x \), where \( \zeta_x \) is the elasticity of brand i’s demand with respect to changes in brand j’s price.
share and revenue than does the CH model. For example, under the TH model, a 25¢ cent decrease in the price of AquaFresh (which has an average sized discrepancy in own price elasticity estimates of .67) increases its market share from the base level of 15.4% to 24.2%, while under the CH model the increase is to about 22.6%. Correspondingly, there are much larger gains in revenues under the TH model (a 61% increase) than under the CH model (53%). Note that these numbers are rather large because the simulation assumes that the price cut is both large and available to all consumers on all purchase occasions. Similar results are found for the other brands.

We also conducted an analysis similar to the optimal coupon exercise of Rossi, et al. (1996). For each household we found the coupon value (price cut) which maximized the posterior expected revenue for a particular brand.⁸ We assume that the manufacturer has a precoupon margin of $0.75 and can overtly discriminate among consumers by offering individual specific coupons in five cent increments. The results discussed again pertain to AquaFresh and are analogous to those found for the other brands. Our findings reveal that the CH model requires larger coupons on average than the TH model since the price elasticities are lower. The median coupon value under CH is 55 cents while under TH it is 50 cents. Perhaps, more importantly, there is little concordance in the households targeted with the largest coupons across the two models. For example, of the 67 households that got a 60¢ coupon (highest value) under CH, less than half (only 28) received a coupon of the same value under TH, with the rest receiving coupons of lesser value. Similar discrepancies were found for other coupon values. Furthermore, while the average value of the coupons is higher in the CH model, the variance in

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⁸ In the interests of brevity we do not provide specifics of the simulation. The reader is referred to Rossi, et al. (1996) for details of the approach.
coupon values is actually lower ($CH = 8\text{¢}, \ TH = 11\text{¢})$. This appears to be a direct consequence of the lower heterogeneity in the posterior price effect observed with the $CH$ model.

In summary, our simulation results reveal that any pricing or couponing strategy that fails to account for preference heterogeneity will likely be seriously flawed. In particular, two important findings emerge: (i) the traditional heterogeneity $TH$ model’s overestimated price sensitivity results in sub-optimally low price and coupon values; and (ii) inaccurate estimation of individual household specific price sensitivities under the $TH$ model leads to inefficient targeting of price sensitive households.

**SUMMARY**

This paper developed a model of consumer brand 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 better account for cross-sectional variation across households, and, consequently, results in more precise estimates of the impact that time-varying marketing variables have on choice. Moreover, model fit is improved more through incorporating this “observed” heterogeneity than through incorporating “unobserved” parameter heterogeneity. In particular, measuring individual specific stated preferences and incorporating this measure into scanner models greatly outperforms trying to approximate these idiosyncratic differences by a specified stochastic formulation.

From a managerial perspective it is important to note that our results imply that standard scanner data models, even those incorporating both unobserved and observed demographic parameter heterogeneity, provide overstated price elasticity estimates due to the omission of brand preference measures. This happens because the price parameter is reduced and the impact of intrinsic brand value is increased when brand preference heterogeneity is explicitly modeled.
and measured. The implication is that a manager relying on standard scanner model results may price their brand sub-optimally. 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.

Similarly, the importance of brand loyalty is overstated in standard scanner models. This occurs because the individual specific nature of the past purchase based loyalty measure erroneously picks up brand preferences in addition to 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. From a managerial perspective this means that since past purchases influence future purchases it is optimal for brands to periodically price promote (Freimer and Horsky 2003). However, our results imply that while this future purchase incentive to promote exists, it is less strong than is implied by standard scanner models.

Ignoring stated preferences in brand choice models also mischaracterizes the heterogeneity in the population. There are two facets of this issue. 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 implications for the efficient targeting of promotion and price discrimination strategies.

While a more complex and expensive data collection process is needed to acquire the joint survey and scanner data required to estimate the model forwarded in this paper, the improved fit, corresponding improved understanding of choice behavior, and the more complete and accurate managerial implications that result make this undertaking worthwhile.
REFERENCES


<table>
<thead>
<tr>
<th>Variable</th>
<th>Arm &amp; Hammer</th>
<th>Aim</th>
<th>Aqua Fresh</th>
<th>Colgate</th>
<th>Crest</th>
<th>Mentadent</th>
<th>Pepsodent</th>
</tr>
</thead>
<tbody>
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<td>Market Share</td>
<td>Mean</td>
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<td>0.0210</td>
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<td>0.3158</td>
<td>0.3240</td>
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<td></td>
<td>Std. Dev.</td>
<td>0.1965</td>
<td>0.2096</td>
<td>0.2018</td>
<td>0.2133</td>
<td>0.2137</td>
<td>0.2581</td>
</tr>
<tr>
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<td>2.3705</td>
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<tr>
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<td>0.2096</td>
<td>0.2018</td>
<td>0.2133</td>
<td>0.2137</td>
<td>0.2581</td>
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<td>Display</td>
<td>Mean</td>
<td>0.0386</td>
<td>0.0663</td>
<td>0.1145</td>
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<td>0.1162</td>
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<td>0.2828</td>
<td>0.2736</td>
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</tr>
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<td>0.4504</td>
<td>0.4459</td>
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<td>2.0261</td>
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<td></td>
<td>Std. Dev.</td>
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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 1-7 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 that $100,000). Family size is the number of individuals in the household.
Table 2
Posterior Means for Coefficients of Traditional Heterogeneity TH Model

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Posterior Mean²</th>
<th>Constant</th>
<th>Family Size</th>
<th>Income</th>
<th>Heterogeneity†</th>
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<td>Arm &amp; Hammer</td>
<td>8.0554</td>
<td>6.9556</td>
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<td>2.5434</td>
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<td>[1.00]</td>
<td>[1.00]</td>
<td>[1.00]</td>
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<tr>
<td>Aim</td>
<td>0.8136</td>
<td>0.3598</td>
<td>0.3375</td>
<td>0.0712</td>
<td>0.9364</td>
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<td></td>
<td>(0.94)</td>
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<td>[0.70]</td>
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<td></td>
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<tr>
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<td>0.3005</td>
<td>1.9467</td>
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<td>[1.00]</td>
<td>[1.00]</td>
<td>[1.00]</td>
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<td></td>
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<tr>
<td>Colgate</td>
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<td>2.7674</td>
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<td>[1.00]</td>
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<tr>
<td>Crest</td>
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<tr>
<td>Mentadent</td>
<td>11.5186</td>
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<td>[1.00]</td>
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<tr>
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<tr>
<td>Loyalty</td>
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<td>[0.49]</td>
<td>(0.98)</td>
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</table>

Ln Marginal Likelihood † -3304.6

† Unobserved heterogeneity is measured by the posterior mean of the square root of the diagonal elements of \( \Sigma^* \) (Rossi, McCulloch and Allenby 1996).

‡ Posterior Means are computed as the average across consumers of the total posterior effects. For example, the posterior mean for price is \( \frac{1}{N} \sum_{i=1}^{N} \{ \theta_i + \delta^* z_i \} \). All means are significantly different from zero.

[ ] Indicates probability that coefficient is positive.
( ) Indicates probability that coefficient is negative.
Table 3
Posterior Means for Coefficients of Complete Heterogeneity CH Model

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Posterior Mean†</th>
<th>Constant</th>
<th>Family Size</th>
<th>Income</th>
<th>Heterogeneity‡</th>
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<tbody>
<tr>
<td>Arm &amp; Hammer</td>
<td>7.686</td>
<td>5.984</td>
<td>0.099</td>
<td>0.173</td>
<td>0.984</td>
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<tr>
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<tr>
<td></td>
<td>[0.91]</td>
<td>(0.51)</td>
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<td></td>
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<tr>
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<td>8.340</td>
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<tr>
<td>Crest</td>
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<td></td>
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<tr>
<td>Mentadent</td>
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<td>[1.00]</td>
<td>[0.99]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price</td>
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<td>-4.505</td>
<td>-0.322</td>
<td>0.137</td>
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</tr>
<tr>
<td></td>
<td>(1.00)</td>
<td>(1.00)</td>
<td>[0.98]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Display</td>
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<td>[0.86]</td>
<td>(0.74)</td>
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<td>0.782</td>
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<td>-0.033</td>
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<td>[1.00]</td>
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<td>Liking</td>
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<td>(0.79)</td>
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</table>

Ln Marginal Likelihood -3149.1

† Unobserved heterogeneity is measured by the posterior mean of the square root of the diagonal elements of Σ* (Rossi, McCulloch and Allenby 1996).
‡ Posterior Means are computed as the average across consumers of the total posterior effects. For example, the posterior mean for price is \( \frac{1}{N} \sum_{i=1}^{N} (\theta + \delta^{\tau^*} \xi_i) \). All means are significantly different from zero.
[ ] Indicates probability that coefficient is positive.
( ) Indicates probability that coefficient is negative.
Table 4
Estimation and Validation Sample Hit Rates†

<table>
<thead>
<tr>
<th>Model</th>
<th>Estimation Sample</th>
<th>Validation Sample</th>
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<tbody>
<tr>
<td>Traditional Heterogeneity Model (TH)</td>
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<td>61.80%</td>
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<tr>
<td>Complete Heterogeneity Model (CH)</td>
<td>73.59%</td>
<td>68.11%</td>
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<tr>
<td>Complete Heterogeneity Model (Imputation Scheme 1)</td>
<td>59.64%</td>
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</tr>
<tr>
<td>Complete Heterogeneity Model (Imputation Scheme 2)</td>
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<td>60.63%</td>
</tr>
</tbody>
</table>

† The hit rate is defined as the percentage of choices predicted accurately.
Table 5
Elasticity Matrix Based on Traditional Heterogeneity (TH) Model ‡

<table>
<thead>
<tr>
<th></th>
<th>A&amp;H</th>
<th>Aim</th>
<th>AquaFresh</th>
<th>Colgate</th>
<th>Crest</th>
<th>Mentadent</th>
<th>Pepsodent</th>
<th>Vulnerability</th>
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<td>0.7827</td>
<td></td>
</tr>
</tbody>
</table>

‡ 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 column wise sum of the cross price elasticities while Vulnerability is the row wise sum.

Table 6
Elasticity Matrix Based on Complete Heterogeneity (CH) Model ‡

<table>
<thead>
<tr>
<th></th>
<th>A&amp;H</th>
<th>Aim</th>
<th>AquaFresh</th>
<th>Colgate</th>
<th>Crest</th>
<th>Mentadent</th>
<th>Pepsodent</th>
<th>Vulnerability</th>
</tr>
</thead>
<tbody>
<tr>
<td>A&amp;H</td>
<td>-4.2760</td>
<td>0.1138</td>
<td>0.6350</td>
<td>1.5359</td>
<td>1.2774</td>
<td>0.5043</td>
<td>0.0964</td>
<td>4.1628</td>
</tr>
<tr>
<td>Aim</td>
<td>0.7629</td>
<td>-3.4692</td>
<td>1.5584</td>
<td>1.8556</td>
<td>2.1797</td>
<td>0.5746</td>
<td>0.2913</td>
<td>7.2225</td>
</tr>
<tr>
<td>AquaFresh</td>
<td>0.3132</td>
<td>0.1085</td>
<td>-2.9474</td>
<td>1.0932</td>
<td>1.2584</td>
<td>0.4085</td>
<td>0.0632</td>
<td>3.2451</td>
</tr>
<tr>
<td>Colgate</td>
<td>0.3262</td>
<td>0.0592</td>
<td>0.4814</td>
<td>-2.8827</td>
<td>1.4909</td>
<td>0.3164</td>
<td>0.0474</td>
<td>2.7216</td>
</tr>
<tr>
<td>Crest</td>
<td>0.2754</td>
<td>0.0688</td>
<td>0.5527</td>
<td>1.4904</td>
<td>-3.0086</td>
<td>0.4276</td>
<td>0.0612</td>
<td>2.8761</td>
</tr>
<tr>
<td>Mentadent</td>
<td>0.2942</td>
<td>0.0506</td>
<td>0.4832</td>
<td>0.8512</td>
<td>1.1623</td>
<td>-3.8719</td>
<td>0.0383</td>
<td>2.8798</td>
</tr>
<tr>
<td>Pepsodent</td>
<td>1.0115</td>
<td>0.4540</td>
<td>1.4019</td>
<td>2.3382</td>
<td>3.1197</td>
<td>0.6680</td>
<td>-4.4659</td>
<td>8.9933</td>
</tr>
<tr>
<td>Clout</td>
<td>2.9833</td>
<td>0.8549</td>
<td>5.1127</td>
<td>9.1645</td>
<td>10.4884</td>
<td>2.8995</td>
<td>0.5978</td>
<td></td>
</tr>
</tbody>
</table>

‡ 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 column wise sum of the cross price elasticities while Vulnerability is the row wise sum.
Figure 1
Distribution of Brand Preferences Across Consumers
Figure 2
Examples of Individual Panel Member Preferences
The bars in the figure depict brands in the following order Arm and Hammer, Aim, AquaFresh, Colgate, Crest, Mentadent and Pepsodent.
Figure 3
Computed Posterior Density Plots for Brand Specific Constants and Intrinsic Brand Values

Note: In the legend, for the CH model, $IV_{ij} = \alpha_{ij} + \omega_iPREF_{ij}$. 
**Figure 4**

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

The vertical lines represent the mean values of the parameters.

**Figure 5**

Density Plots for the Posterior Price Coefficient \( \theta \)

The vertical lines represent the mean values of the parameters.