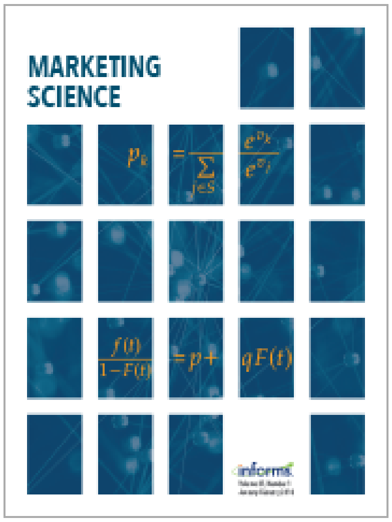

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Sandeep R. Chandukala, Yancy D. Edwards, Greg M. Allenby,

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Identifying Unmet Demand

Sandeep R. Chandukala
Kelley School of Business, Indiana University, Bloomington, Indiana 47405, sarchand@indiana.edu

Yancy D. Edwards
School of Business, Saint Leo University, Saint Leo, Florida 33574, yancy.edwards@saintleo.edu

Greg M. Allenby
Fisher College of Business, Ohio State University, Columbus, Ohio 43210, allenby.1@osu.edu

Brand preferences and marketplace demand are a reflection of the importance of underlying needs of consumers and the efficacy of product attributes for delivering value. Dog owners, for example, may look to dog foods to provide specific benefits for their pets (e.g., shiny coats) that may not be available from current offerings. An analysis of consumer wants for these consumers would reveal weak demand for product attributes resulting from low efficacy, despite the presence of strong latent interest. The challenge in identifying such unmet demand is in distinguishing it from other reasons for weak preference, such as general noninterest in the category and heterogeneous tastes. We propose a model for separating out these effects within the context of conjoint analysis, and we demonstrate its value with data from a national survey of toothpaste preferences. Implications for product development and reformulation are explored.

Key words: unmet demand; heterogeneous variable selection; conjoint analysis; Bayesian hierarchical model
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1. Introduction

Preference for a product offering is determined by the expected benefits that accrue from its use. These benefits are a function of both the importance of the underlying motivations that drives an individual to the marketplace looking for assistance and the efficacy of the product attributes in meeting the individual's needs (Patrick 1997). Despite the best attempts by firms to anticipate and respond to the motivating wants of consumers, the possibility always exists that some aspects are either poorly met or unmet by the current array of marketplace offerings. There is no guarantee that the supply of product offerings is best positioned to respond to the concerns and interests of individuals as they engage in the tasks of everyday life (Fennell and Allenby 2002, cf. Kennedy and Ehrenberg 2001), despite marketing's best efforts to guide management to make what people will want to buy. Unmet demand results when the brands within the product category are perceived as ineffective at meeting consumers' needs.

A challenge in measuring unmet demand is distinguishing it from the many other reasons that can account for low sales, including the obvious reason that prices are too high, existing offerings do not have the right combination of attributes, or particular attributes are irrelevant to an individual. For these and other reasons, marketing researchers rely on conjoint analysis to assess potential demand for offerings (Green and Srinivasan 1978, Louviere and Woodworth 1983, Haijer et al. 1998). Conjoint analysis facilitates the measurement of consumer value for the attributes and benefits of hypothetical offering so that their levels can be optimally set in anticipation of marketplace competition. The attributes and attribute levels are used by firms to emphasize their advertising (short-run) and product development (long-run) strategies (Green and Krieger 1995). In this paper, we develop a new model of heterogeneity that can be used in conjoint analysis, and in other models of choice, to identify unmet demand.

Our model of heterogeneity extends the conventional random-effects model through the combination of three features: (i) a normal component mixture model that allows for different response segments (Allenby et al. 1998), (ii) heterogeneous variable selection that is sensitive to the possibility that only a few attributes are of any importance to a specific respondent (extending Gilbride et al. 2006), and (iii) the presence of covariates whose relationship to the model parameters can be segment specific (Lenk and DeSarbo 2000). Our normal component variable selection model allows for the presence of distinct response segments characterized by a subset of model parameters being nonzero, each having a potentially unique relationship to the covariates. Thus, the response segments are more meaningfully and specifically defined than in a standard normal component model, providing for a richer interpretation of heterogeneity. A unique feature of our model is that the covariate relationship in (iii) above is determined almost entirely by attribute levels that are of some importance to each respondent, not by levels that are unimportant. By removing the influence of unimportant or unattended attribute levels, we find a much stronger covariate relationship to model parameters. Moreover, we find that including their influence distorts estimated relationships.

We apply our model to conjoint data collected in a national study of toothpaste preferences and find large improvements in model fit from the three components. We relate part-worth coefficients to covariates describing discomfort in the use of the product (e.g., tastes too strong, scratches enamel, costs too much), and views of overall efficacy (e.g., does not work) of offerings in the category, and we find evidence of a large segment of respondents who appear to have minimal interest in toothpaste attributes and benefits. For those respondents who are more engaged, a strong relationship to the covariates is detected. Interestingly, we find that the components of our model account for many of the random-effects covariances, implying that joint preferences for attribute levels in our conjoint analysis is due to nonzero part-worths, not the extent of preference. Finally, we find sizable and robust implications for responding to unmet demand.

The remainder of this paper is organized as follows. Section 2 presents our normal component variable selection for heterogeneity and discusses challenges in estimation. Section 3 describes the data used in the analysis, and §4 reports parameter estimates and model fit. Section 5 discusses implications for detecting and responding to unmet demand, and §6 offers concluding remarks.

2. A Model for Unmet Demand

We define unmet demand as the result of competing forces. We assume that there is a primary motivation or need that drives an individual to want a particular benefit that may or may not be realized though the available product attributes and their levels (Allenby et al. 2002, Yang et al. 2002). An individual may be troubled by stains on his or her teeth as a result of items he or she recently ate or drank but may feel that the whitening powers of toothpastes are ineffective at offering a solution. Swimmers may have great need for repairing damaged hair but may feel that existing conditioners do not leave their hair feeling restored. Similarly, parents cooking dinner for a busy family may be unsatisfied with the currently available options for healthy and tasty meals that are easy and quick to prepare. The common theme in each of these scenarios is the presence of a motivational state in search of an effective instrument for change.

Our model for unmet demand is essentially a model of heterogeneity. It describes the variation of model coefficients across a population for those respondents who express some evidence of a primary motivation. The presence of the primary motivation manifests itself through nonzero coefficient values for product attributes moderated by the individual's belief about product efficacy. Thus, our model is different from other models of unmet demand (Anupindi et al. 1998, Kalyanam et al. 2007) that focus on the effects of stockouts and product nonavailability, where consumers substitute to other goods. It also differs from models in which "demand" is measured through a marketplace transaction. We operationalize demand as a motivating force that may result in an actual purchase.

We include consumer beliefs about product efficacy in our analysis, as was originally suggested by Green and Rao (1971) and pursued by others who have introduced attitudinal (Ashok et al. 2002) and subjective characteristics (Luo et al. 2008) into models of choice. In these models, a factor structure is assumed that directly affects overall utility and purchase intention. Our model does not assume a factor structure but assumes that beliefs moderate the magnitude of nonzero model coefficients only. These coefficients correspond to preference for product attribute levels, not overall utility, and are therefore more diagnostic.

Our model for unmet demand begins with a random-effects specification for heterogeneity (Lenk et al. 1996, Allenby and Ginter 1995):

$$\beta_h = \Gamma' z_h + \varepsilon_h, \tag{1}$$

where h indexes the respondent, β is a vector of model coefficients, z_h is a vector of product beliefs, and ε_h is a vector of random-effects reflecting unobserved heterogeneity. The matrix of coefficients Γ describes the variation of the model coefficients associated with variation in product beliefs. We expect larger coefficient values for respondents who have positive beliefs about product efficacy and smaller coefficient values for respondents who do not believe that attributes are effective at addressing their needs. Our goal is to accurately estimate Γ.

Beliefs have been used to explain a variety of aspects of consumer judgment and decision making. Brucks (1985), for example, relates product category beliefs to search behavior, and Bettman and Park (1980) view beliefs in terms of a person's prior knowledge of brand performance. Beliefs are propositions that link objects to attributes, and it is natural to incorporate them into models of heterogeneity as in Horsky et al. (2006). However, a complication arises in the estimation of Γ when consumers attend to only a subset of the elements of the model coefficients. In a conjoint analysis, it is common for the coefficient vector, β, to be of high dimension, with a small subset of the model coefficients of any importance to a specific respondent. Thus, elements of the coefficient vector may be small because of an underlying need state rather than a belief of an attribute being ineffective.

Models of variable selection have been used extensively in statistics (George and McCulloch 1993, Geweke 1996, Clyde and George 2004) and more recently in marketing (Gilbride et al. 2006, Fong and DeSarbo 2007). We incorporate variable selection into the model using a model of heterogeneous variable selection (Gilbride et al. 2006) by defining a diagonal matrix C whose elements take on a value of either one or a small positive constant c:

$$C_h = \operatorname{diag}(\tau_h), \quad \text{where} \\ \tau_{hj} \sim \text{Binomial}(\theta_j) \text{ taking on values } (1, c). \tag{2}$$

Combining (2) with (1), we obtain a model of heterogeneity that effectively nullifies specific elements of the coefficient vector:

$$\beta_h = C_h \Gamma' z_h + C_h \varepsilon_h. \tag{3}$$

The inclusion of the matrix C_h in the model specification avoids a "regression to the mean," or "shrinkage" effect present in models of heterogeneity. When a particular element of β_h is measured imprecisely, typically because of the lack of individual-level data, posterior estimates in model (1) are shrunk toward the posterior mean of $\Gamma' z_h$ of the random-effects distribution. For model (3), they are shrunk toward the posterior mean of $C_h \Gamma' z_h$ with elements equal to either a small constant or the corresponding element of $\Gamma' z_h$, depending on the posterior distribution of the vector τ_h. When there is too little respondent-specific information in the data about an element of β_h, its posterior distribution is near zero. When there is much information, the posterior distribution moves away from zero. Thus, in Equation (3), the default condition is that a coefficient is expected to be close to zero unless there is evidence of the coefficient's significance in the data. This aspect of the model is important for measuring unmet demand because it requires evidence of the existence of the primary motivation for a coefficient to be nonzero.

The advantage of using Equation (3) to estimate Γ is that much greater weight is given to those respondents with nonzero coefficients. If posterior estimates of β_h are near zero, then so are the corresponding elements of τ_h, resulting in little available information for estimating Γ since (3) holds for any of its values. The information for estimating Γ comes from the larger values of β_h, corresponding to τ_h equal to one. Thus, the estimates of Γ in Equation (3) describe the relationship between the coefficients β_h and the covariates z_h for those instances where a respondent's behavior is affected by the variables, not when the variables play no role. In a conjoint analysis, these are the attribute levels that affect choice.

It is useful to write Equation (3) in an alternative form to more clearly see the effects of the variable selection matrix C_h on the distribution of heterogeneity:

$$\beta_h^* = C_h^{-1} \beta_h = \Gamma' z_h + \varepsilon_h. \tag{4}$$

Here, the elements of the vector β_h^* have been filled out by the matrix C_h^{-1}. When there exists little information in the data about a specific element of β_h^*, posterior estimates will be centered at $\Gamma' z_h$ with uncertainty determined by ε_h. We employ a multivariate Normal distribution for the random effects and introduce a mixture component model to allow for possibly distinct response segments:

$$\beta_h^* = C_h^{-1} \beta_h \sim \sum_{k=1}^{K} \varphi_k \mathrm{N}(\Gamma_k' z_h, \Sigma_k), \tag{5}$$

where k indexes the response segments of size φ_k, with segment-specific coefficient matrix Γ_k and covariance matrix Σ_k.

Equation (5) extends the heterogeneous variable selection model of Gilbride et al. (2006) (we refer to the reference hereafter as GAB) by introducing covariates, z_h, into the model specification and introducing a latent normal component structure. This structure is particularly useful for identifying unmet demand because the key parameters Γ_k, describing the variation of model coefficients with brand beliefs, are determined only by those variables playing a nontrivial role in describing behavior.

An intuitive understanding of the three model components is provided in Figure 1. Equation (1) is a standard model of heterogeneity in which the coefficient matrix Γ describes the relationship between the model coefficient vector (β_h) and the covariates (z_h) for all values of the covariate. The variable selection portion of the model in Equations (2) and (3) allows the coefficient matrix to describe only on nonzero values of the coefficient vector. When β_h is near zero, the corresponding diagonal elements of C_h are also near zero and Equation (3) is true for nearly any value of Γ. The coefficient matrix Γ is therefore uninformed by the elements of β_h near zero. Finally, the mixture component portion of the model allows for distinct response segments. In our model, it is as if the zero coefficient elements are removed from the analysis for estimation of Γ. This aspect of the model is important for measuring unmet demand where, by definition, we assume the presence of a primary force that is moderated by the covariate value. Including the zero-valued elements would distort the estimated relationship.

Figure 1 Model Overview

Covariate relationship	
$\beta_h = \Gamma' z_h + \varepsilon_h$	Γ measures the relationship between β and z.
Variable selection	
$\beta_h = C_h \Gamma' z_h + C_h \varepsilon_h$ $C_h = \text{diag}(\tau_h)$, where $\tau_{hj} \sim \text{Binomial}(\theta_j)$ taking on values $(1, c)$.	Γ measures the relationship between β and z for nonzero coefficients.
Mixture components	
$\beta_h = \sum_{k=1}^{K} \varphi_k \text{N}(C_h \Gamma_k' z_h, C_h \Sigma_k C_h')$	Γ_k measures the relationship between β and z for nonzero coefficients in each segment (k).

Finally, it is important to note that we rely on the cross-sectional relationship between β_h and z_h to identify unmet demand. At the disaggregate level, we can only infer about the single posterior distribution of a respondent, β_h, which is similar to having just one "observation" in an analysis. Hence, we cannot distinguish between low interest and unmet demand, and we must rely on cross-section covariation with z_h to infer where demand is being poorly met. Our model implicitly assumes that the respondents provide exchangeable information about unmet demand for nonzero elements of their coefficient vector (see Bernardo and Smith 1994), an assumption typically made in random-effects models for all model coefficients.

2.1. Bayesian Estimation

Bayesian estimation of the model of heterogeneity is carried out using the method of data augmentation in which a latent variable, s_h, is introduced, which points to respondent segment membership. When s_h is known, estimation is greatly simplified and closely follows the GAB algorithm. Bayesian estimation requires the assumption of a prior distribution for all model parameters, including a prior for the segment-specific variable selection parameters:

$$\theta_{j,k} \sim \text{Beta}(a, b), \tag{6}$$

where j indexes the elements of the coefficient vector β_h. The posterior conditional distribution of the latent augmented variable s_h is distributed multinomial with segment probabilities proportional to

$$\begin{aligned} &[s_h = k \mid \beta_h, C_{h,k}, \Gamma_k, \Sigma_k, \theta_k, \varphi_k] \\ &\quad \propto \text{Normal}(C_{h,k}^{-1}\beta_h \mid \Gamma_k' z_h, \Sigma_k) \times \varphi_k \\ &\quad \times \prod_{j=1}^{J} \text{Beta}(C_{j,k} \mid \theta_{j,k}). \end{aligned} \tag{7}$$

The factor on the far right of (7) is due to incorporating heterogeneous variable selection within a normal component mixture model, distinguishing it from standard component mixture models (see Rossi et al. 2005). In addition, as discussed in GAB, the draw of τ, which determines whether an element of β_h is shrunk toward zero or not, is determined in part by the likelihood of each respondent's data. As near-zero values of β_h are more likely to explain a respondent's data, the greater the likelihood of τ_{hj} taking on a small value, c. Details are provided in the appendix.

3. Empirical Application

Data are from a national sample of 757 respondents investigating the preferences for toothpaste. A portion of the survey involved a conjoint study of 30 toothpaste attributes and benefits (a/b) and their levels, which are displayed in Table 1. The levels were originally identified through a series of focus group studies. Data were also collected on a scale from 1–5, reflecting agreement with statements about the product category, which are described below. Attributes and benefits (a/b) were described in a manner similar to brand claims found on toothpaste packaging and media advertising, and they include attributes related to the physical formation of the offering and psychological attributes constructed by marketing efforts and benefits sought from product use.

Ten sets of stimuli (see Table 2) were presented, with each comprising four hypothetical product offerings described by three attribute levels, or benefits (a/b). Respondents were told that the a/b items not listed in the description were the same for the offerings (cf. Bradlow et al. 2004). For a ranking conjoint task, the distributional assumptions lead to an exploded logit form of complete preference ordering (Chapman and Staelin 1982). The likelihood of the rank ordering for the four triplets in one of the sets is equal to

$$\Pr(U_{1m} > U_{2m} > U_{3m} > U_{4m})_h = \prod_{i=1}^{3} \frac{\exp(x_{im}'\beta_h)}{\sum_{j=i}^{4} \exp(x_{jm}'\beta_h)}, \tag{8}$$

where U_{1m} is the utility of the hypothetical product offering with the highest rank in the mth set, x_{im} is the dummy variable coding of the a/b for the ith ranked offering in set m, and β_h is the vector of a/b importance weights (part-worths) for respondent h. The likelihood for an individual's ranks is defined across all 10 triplets:

$$\begin{aligned} \text{L}(\beta_h \mid \text{Data}) &= \prod_{m=1}^{10} \Pr(U_{1m} > U_{2m} > U_{3m} > U_{4m})_h \\ &= \prod_{m=1}^{10} \prod_{i=1}^{3} \frac{\exp(x_{im}'\beta_h)}{\sum_{j=i}^{4} \exp(x_{jm}'\beta_h)}. \end{aligned} \tag{9}$$

Heterogeneity is incorporated into the model specification by assuming a random-effects distribution described in its most general form by Equation (5).

Table 1 Toothpaste Attributes and Benefits

Attribute/benefit	Description
	Medical benefits
b1	Helps prevent cavities
b2	Delivers protection in hard-to-reach places
b3	Helps remove tartar and plaque
b4	Helps promote healthy gums
b5	Penetrates to strengthen your teeth against cavities
b6	Helps fight germs and infections in your mouth
	Taste
b7	Mild tasting
b8	Fresh tasting
b9	Gives your mouth a tingle
b10	A taste kids love
b11	Great bubbling action
	Abrasiveness
b12	Doesn't irritate your mouth
b13	For sensitive teeth
b14	Safe for tooth enamel (nonscratching)
	Resulting appearance
b15	Helps clean teeth
b16	Helps remove stains
b17	Whitens your teeth
b18	Makes your teeth gleam like pearls
	Resulting breath
b19	Fights bad breath
b20	Freshens breath for 12 hours
b21	Helps take away morning mouth
	Price
	Regular price[a]
b22	20% less
	Ingredients
	80% natural/20% artificial ingredients[a]
b23	100% natural ingredients
	Packaging
	80% recyclable packaging[a]
b24	100% recyclable packaging
	Interests
b25	An interesting way to clean your teeth
b26	Provides a change of pace
	Social
b27	Shows others you care about your teeth
b28	Helps you feel good about yourself for brushing regularly
	Maintenance
b29	For everyday brushing
b30	For routine maintenance

[a]Null condition.

Six product beliefs, displayed in Table 3, comprise the vector z_h. Some belief statements concern specific attributes (e.g., taste, price), whereas others refer to toothpastes in general. Attribute-specific beliefs are worded to reflect discomfort in using the product. Category beliefs are worded to reflect frustration with the outcome from using toothpaste and were collected before the conjoint exercise and reflect prior knowledge. Respondents indicated their belief strength to the statements in Table 3 by indicating whether the statement described them or their belief completely, very well, somewhat, slightly, or not at all. The numerical assignment for "not at all" is 0, "slightly" is 1, "somewhat" is 2, "very well" is 3, and "completely" is 4. We treat these variables as continuous in our analysis, and we leave for future research the investigation of their treatment as ordinal scores.

Table 3 provides the responses and summary statistics to the product belief statements. Seventy-four percent responded that the statement "Toothpastes irritate my mouth" does not describe them, and less than 1% said the statement completely describes them. Just over 18% of the respondents marked that the statement "Toothpaste breath freshening doesn't last long enough" completely describes them, and less than 10% do not ascribe to that statement. The belief data indicate that there is heterogeneity in consumers' beliefs about toothpaste attributes.

4. Parameter Estimates

Markov chain Monte Carlo (MCMC) methods are used to estimate the model parameters (see Rossi et al. 2005, Chib and Greenberg 1995). The chain was run for a total of 50,000 iterations, with parameter estimates based on the last 5,000 iterations. We investigate multiple start points and found the chain to converge to a common posterior distribution. The estimation algorithm for the best-fitting model is provided in the appendix. Product beliefs were entered in mean-centered form, so that the intercept term reflected part-worth importance for respondents with average beliefs.

4.1. Alternative Models

We investigate eight variations of the distribution of heterogeneity whose most general form is expressed in Equation (5). Fit statistics, measured in terms of the marginal density of the data, are reported for all models in Table 4. The first model is a standard random-effects model, and the second model adds product beliefs to this standard specification as in Rossi et al. (2005). Model 3 is the heterogeneous variables selection model of Gilbride et al. (2006). Model 4 adds covariates to the model 3 specification, and models 5 and 6 are based on a normal component mixture specification with unique component intercepts, $\bar{\beta}_k$. Finally, models 7 and 8 combine covariates (product beliefs), normal components, and variable selection into one model. In model 7, the relationship of the covariates (z_h) is assumed constant across components, and in model 8 the relationship is allowed to be unique for each of the mixing components.

Table 2 Example Stimuli for Measuring the Importance of Attribute Levels

Think back to the last time you brushed your teeth. Let's assume you had to choose a specific toothpaste for this toothbrushing occasion. If you had to choose among the four toothpaste products described below, please indicate which would be your **most** preferred choice by writing a "4" in the box below that one. Then choose your next most preferred and write a "3" below that and so on, marking a "1" beneath your **least** preferred choice. Assume all features not listed are the same across the choices.

QUESTION 1

Toothpaste 53	Toothpaste 28	Toothpaste 31	Toothpaste 75
Helps prevent cavities	Delivers protection in hard-to-reach places	Helps remove tartar and plaque	Helps promote healthy gums
A taste kids love	Gives your mouth a tingle	Fresh tasting	Mild tasting
Doesn't irritate your mouth	For sensitive teeth	Safe for tooth enamel (nonscratching)	Doesn't irritate your mouth
____	____	____	____

Table 3 Responses to Toothpaste Beliefs: "Describes Me…/Describes My Beliefs…"

Belief	Not at all	Slightly	Somewhat	Very well	Completely	Mean	Std. dev.
z_1: Toothpastes are too strong tasting.	290	202	194	52	19	1.09	1.065
z_2: Toothpastes scratch the enamel on my teeth.	454	173	101	24	5	0.62	0.880
z_3: Toothpastes irritate my mouth.	563	112	59	17	6	0.40	0.792
z_4: Toothpastes cost too much.	249	202	157	97	52	1.34	1.246
z_5: Toothpaste breath freshening doesn't last long enough.	79	126	229	184	139	2.24	1.228
z_6: Toothpastes don't really work to prevent dental problems.	213	194	223	99	28	1.39	1.134

4.2. Model Fit Statistics

Table 4 provides the in-sample and out-of-sample fit statistics for all eight models. We find that model 7 has the best in-sample fit based on comparison of the log-marginal densities, as suggested by Newton and Raftery (1994). Moreover, we find that just two components are sufficient for this model. When we specify a greater number of mixing components, the MCMC algorithm gives nonnegligible mass to only two components. The size of the mixing components is 0.70 for the first component (528 respondents) and 0.30 for the second component (229 respondents). We also find large changes in the marginal density across models, indicating that the data are informative for distinguishing among the models.

We employ hit rate and hit probability to assess out-of-sample fit. Hit rate is defined as the posterior mean of correct predictions for the entire rank ordering for one holdout choice for each individual averaged across all respondents. Hit probability is defined as the posterior mean of the predicted probability for the most preferred alternative. We find that model 7 has the best predictive fit. As discussed in GAB we find that models with variable selection have a good predictive fit. We find that the best-fitting model (model 7) results in a 17% improvement over the baseline model (model 2).

4.3. Parameter Estimates

Parameter estimates for the mean of the mixing distributions for model 7, the best-fitting model, are reported in Table 5. Reported is the posterior mean of the parameters when the covariates z_h are at their average values. Also reported are posterior estimates of $\theta_{j,1}$ and $\theta_{j,2}$, which reflect the proportion of respondents who give nonzero weight to each of the attribute levels when providing their responses. We find that estimates (posterior means) for the first mixture component are almost always greater in magnitude than estimates for the second component. We also find that values of $\theta_{j,2}$ are much smaller than estimates of $\theta_{j,1}$. Both findings indicate that the second component reflects responses that are less dependent on the attribute levels of the product description than responses and respondents assigned to the first component. This may be due to many factors, such as disengagement from the data collection exercise, cognitive errors and constraints, or possible noninterest in the product category that results in low estimates of $\theta_{j,2}$ across most of the attributes and benefits. Responses in the first mixing component are much more sensitive to toothpaste attributes and their levels.

Figure 2 compares estimates of diagonal and off-diagonal elements of the covariance matrices for models 2 and 7. The plots in the left portion of the figure compare diagonal elements of the covariance matrix of random effects, with estimates from the first model plotted on the horizontal axis and estimates from the best-fitting model appearing on the vertical axis. A 45-degree line is added for interpretation. The top plots correspond to the covariance matrix for the first mixing component plotted on the vertical axis, and the bottom plots are for the second mixing component of less engaged respondents. The plots in the right portion of the figure compare off-diagonal elements of the covariance matrices of random effects.

Table 4 Model Fit

Model of heterogeneity	Description	Log-marginal density	Out of sample: Hit rate	Out of sample: Hit probability
1 Intercept model	$\beta_h = \alpha + \varepsilon_h$	−19,090.11	0.31	0.42
2 Covariate model	$\beta_h = \Gamma' z_h + \varepsilon_h$	−18,976.53	0.35	0.48
3 Intercept model with variable selection	$\beta_h \sim \mathrm{N}(C_{\tau h \bar{\beta}, C_{\tau h} V_\beta C_{\tau h}})$	−18,342.52	0.33	0.46
4 Covariate model with variable selection	$\beta_h \sim \mathrm{N}(C_{\tau h}\Gamma' z_h, C_{\tau h} V_\beta C_{\tau h})$	−18,146.64	0.36	0.49
5 Normal component mixture model	$\beta_h \sim \sum_{k=1}^{K} \varphi_k \mathrm{N}(\bar{\beta}_k, \Sigma_k)$	−18,446.34	0.32	0.44
6 Normal component mixture model with covariates	$\beta_h \sim \Gamma' z_h + \sum_{k=1}^{K} \varphi_k \mathrm{N}(\bar{\beta}_k, \Sigma_k)$	−18,009.11	0.34	0.46
7 Normal component mixture model with variable selection and common covariate relationship	$C_{\tau h}^{-1}\beta_h \sim \Gamma' z_h + \sum_{k=1}^{K} \varphi_k \mathrm{N}(\bar{\beta}_k, \Sigma_k)$	**−17,572.72**	0.41	0.53
8 Normal component mixture model with variable selection and unique covariate relationship	$C_{\tau h}^{-1}\beta_h \sim \sum_{k=1}^{K} \varphi_k \mathrm{N}(\Gamma_k' z_h, \Sigma_k)$	−17,987.63	0.36	0.49

The plots indicate that the normal mixture model with variable selection (model 7) has much smaller diagonal elements and off-diagonal elements that are very close to zero. That is, the presence of covariances in a standard model of heterogeneity appear to be largely due to an attribute level being of any importance to a respondent versus not important, not the extent of importance. It also appears that a large amount of detected heterogeneity is due to "noise" from respondents who are disengaged from the decision process. The dominant presence of zero off-diagonal covariance elements in model 7, coupled with large improvements in model fit, indicates that the model is successfully explaining heterogeneity, reducing that which is commonly called "unobserved."

The presence of a common coefficient matrix is consistent with the small parameter estimates reported in Table 5 for the second mixing component. It indicates that the data cannot support the estimation of a distinct coefficient matrix. For the respondents who are responsive to the changing attributes and levels describing the product offerings, we find many large coefficient estimates relating attribute-level part-worth to the product beliefs about product cost and efficacy. Estimates of the coefficient matrix Γ in model 6 are much different than that from model 2, with a correlations coefficient of only 0.16. Coefficient matrices for these and other models are available from the authors upon request.

5. Discussion

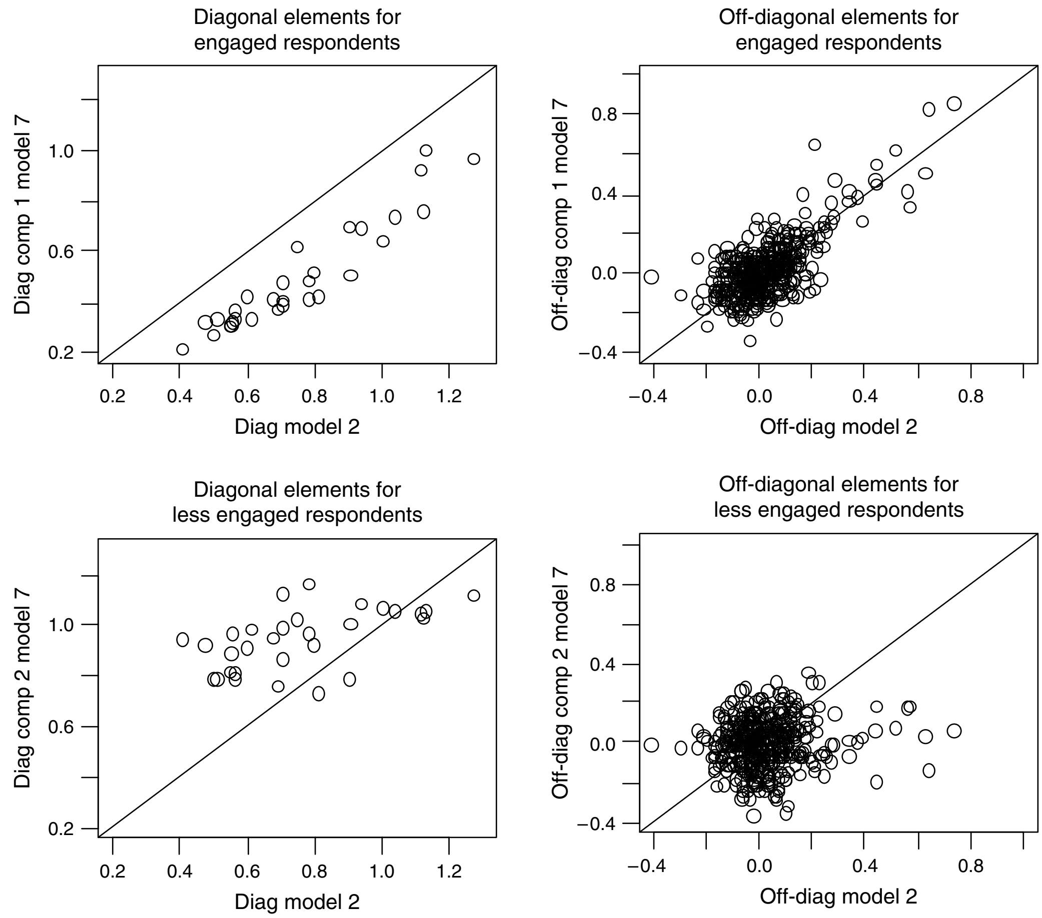
Unmet demand results when the brands within the product category are perceived as ineffective at meeting consumers' needs. We identify the presence of unmet demand with the coefficient matrix Γ. In our conjoint study we have 11 product components (e.g., medical benefits, taste, abrasiveness, resulting appearance, resulting breath), each composed of 2 to 6

Table 5 Posterior Estimates of the Mean of the Normal Components and Variable Selection Probability

Attribute/benefit	$\bar{\beta}_1$	$\bar{\beta}_2$	θ_{*1}	θ_{*2}
b1	**0.13**	**−0.29**	**0.54**	**0.13**
b2	**−2.16**	**−0.66**	**0.56**	**0.07**
b3	**2.24**	0.14	**0.40**	0.05
b4	**0.75**	**0.54**	**0.29**	0.03
b5	**0.63**	**0.40**	**0.28**	**0.06**
b6	**−1.72**	**−0.35**	**0.46**	**0.07**
b7	**1.73**	**−0.84**	**0.18**	0.03
b8	**2.23**	**1.16**	**0.16**	**0.10**
b9	**1.29**	**0.51**	**0.31**	0.02
b10	**−3.26**	**−0.82**	**0.74**	**0.18**
b11	**−2.06**	**−0.73**	**0.52**	**0.14**
b12	**−0.66**	−0.29	**0.12**	0.04
b13	**−0.76**	−0.05	**0.58**	0.04
b14	**1.80**	**0.45**	**0.22**	**0.07**
b15	**0.53**	**−0.28**	**0.31**	0.04
b16	**0.10**	**−0.59**	**0.31**	0.04
b17	**1.25**	−0.24	**0.20**	0.02
b18	**−1.99**	**−0.58**	**0.73**	**0.10**
b19	**−0.35**	**0.32**	**0.23**	0.04
b20	**1.15**	0.07	**0.31**	**0.07**
b21	**−0.56**	**−0.31**	**0.19**	0.02
b22	**1.47**	**0.39**	**0.46**	**0.08**
b23	**2.02**	**0.44**	**0.62**	**0.16**
b24	**1.67**	**0.26**	**0.16**	0.05
b25	**−0.77**	**0.49**	0.15	0.03
b26	−0.27	−0.01	**0.33**	0.03
b27	**−2.49**	**−0.66**	**0.35**	**0.17**
b28	**2.16**	**0.61**	**0.41**	**0.12**
b29	**−0.43**	**0.67**	**0.39**	**0.06**
b30	−0.09	**−0.77**	**0.36**	0.05

Note. Estimates in bold have more than 95% of their posterior mass away from zero.

Figure 2 Comparison of Covariance Matrices for Engaged and Less Engaged Respondents



attributes and benefits, totaling 30. As is common in conjoint analysis, we focus on the part-worths relative to a baseline condition. The medical benefits component, attribute b1, "Helps prevent cavities," is considered the base level all toothpastes possess within that component, and other benefits are viewed as enhancements. Similarly, the resulting appearance component, b15, "Helps clean teeth," is the base level all toothpastes possess in that component and so on. We study the contrast of the attribute and benefit to its associated base level within its component by differencing the rows of the Γ matrix to measure the added value of product enhancements (e.g., b2 − b1) to the covariates z_h.

Table 6 displays the covariate relationship for the medical benefit component. A negative coefficient indicates that increased agreement with the belief statement in Table 3 is associated with a decline in the magnitude of the contrast; i.e., respondents see less value in product enhancements. Negative coefficients point to the condition of unmet demand for respondents in agreement with the belief statement. Respondents not in agreement with the belief statement are expected to have greater value for the enhanced level of a/b relative to the baseline condition. In contrast, positive coefficients indicate that demand is being met through the levels of an a/b. Respondents who are in agreement with belief statements value the levels of an a/b more. Positive coefficients point to where underlying latent demand is currently being met.

Unmet demand for medical benefits is associated with beliefs that toothpastes are too strong tasting (z_1), irritate one's mouth (z_3), cost too much (z_4), and generally do not work (z_6). Respondents

Table 6 Unmet Demand for Medical Benefits

a/b	Strong tasting (z_1)	Scratch enamel (z_2)	Irritate my mouth (z_3)	Cost too much (z_4)	Breath freshening doesn't last long (z_5)	Don't really work to prevent dental problems (z_6)
b2	**−0.49**	**0.28**	**−0.27**	**−0.71**	**0.16**	**−0.66**
b3	**−0.16**	**0.44**	−0.03	**−0.51**	**−0.11**	**−0.40**
b4	**−0.19**	**0.43**	**−0.10**	**−0.27**	0.11	**−0.87**
b5	0.16	**0.20**	**−0.23**	**−0.27**	**−0.41**	**−0.27**
b6	**−0.29**	0.02	**−0.53**	**−0.36**	0.03	**−0.58**

Note. Estimates in bold have more than 95% of their posterior mass away from zero.

who agree with these beliefs tend to have smaller part-worths for enhanced levels of the medical benefits attributes. In contrast, concerns about tooth enamel (z_2) and breath freshening (z_5) are found to express themselves in heightened levels of demand for the medical benefits. Concerns about scratched tooth enamel are associated with demand for toothpastes that deliver protection in hard-to-reach places (b2), promote healthy gums (b4), and the strengthen teeth (b5). We note that the magnitude of the coefficient contrasts is large, given that the part-worths are measured using a logit model, and the beliefs are collected on a five-point rating scale.

Table 7 displays the covariate relationship for the taste component. We find evidence of unmet demand for the contrasted a/b of the taste component when toothpastes are believed to be too strong tasting (z_1), scratch one's enamel (z_2), irritate one's mouth (z_3), and generally do not work to prevent dental problems (z_6). However, demand is met by the contrasted a/b of taste when it is believed that breath freshening does not last long enough (z_5). That is, respondents are more likely to value the heightened level of the taste attributes (e.g., fresh tasting, gives your mouth a tingle) even though they believe that these benefits do not last long enough. This association suggests that even though demand is being met, it might be further met by tastes that last longer in addition to immediate taste sensations such as "fresh" or "gives your mouth a tingle."

Table 8 displays the covariate relationship for the abrasiveness component. Here, we do not find evidence of unmet demand that corresponds to a negative coefficient. Instead, we find evidence of demand that is met through toothpastes for sensitive teeth (b13) when respondents believe that toothpastes scratch tooth enamel (z_2) and when toothpastes are believed not to work at all (z_6). Similarly, preference for the nonscratching tooth enamel benefit (b14) is sought by respondents who believe that toothpaste is too strong tasting (z_1) and by those who believe that toothpastes do not really work (z_6).

Table 9 displays the covariate relationship for the appearance component. We find evidence of met demand for heightened levels of this component for stain removal (b16), teeth whitening (b17), and the ability to make your teeth gleam like pearls (b18).

Table 7 Unmet Demand for Taste

a/b	Strong tasting (z_1)	Scratch enamel (z_2)	Irritate my mouth (z_3)	Cost too much (z_4)	Breath freshening doesn't last long (z_5)	Don't really work to prevent dental problems (z_6)
b8	**−0.40**	**−0.75**	**−0.42**	−0.19	0.18	**−0.68**
b9	**−0.37**	**−0.54**	**−0.75**	**0.60**	**0.69**	**−0.37**
b10	**−0.62**	0.26	**−0.92**	**0.57**	**0.71**	**−0.82**
b11	**−0.21**	**−1.11**	0.28	**−0.37**	**0.28**	**−0.95**

Note. Estimates in bold have more than 95% of their posterior mass away from zero.

Table 8 Unmet Demand for Abrasiveness

a/b	Strong tasting (z_1)	Scratch enamel (z_2)	Irritate my mouth (z_3)	Cost too much (z_4)	Breath freshening doesn't last long (z_5)	Don't really work to prevent dental problems (z_6)
b13	−0.30	**0.66**	−0.15	**0.26**	**0.33**	**0.76**
b14	**0.31**	**0.29**	**0.41**	−0.19	−0.06	**0.34**

Note. Estimates in bold have more than 95% of their posterior mass away from zero.

Table 9 Unmet Demand for Appearance

a/b	Strong tasting (z_1)	Scratch enamel (z_2)	Irritate my mouth (z_3)	Cost too much (z_4)	Breath freshening doesn't last long (z_5)	Don't really work to prevent dental problems (z_6)
b16	**0.22**	**0.11**	0.08	0.09	−0.17	**0.20**
b17	**0.24**	**0.53**	**0.11**	**0.14**	**−0.13**	**0.21**
b18	**0.11**	**0.22**	**0.41**	0.09	0.08	**0.19**

Note. Estimates in bold have more than 95% of their posterior mass away from zero.

Table 10 Unmet Demand for Breath Freshening

a/b	Strong tasting (z_1)	Scratch enamel (z_2)	Irritate my mouth (z_3)	Cost too much (z_4)	Breath freshening doesn't last long (z_5)	Don't really work to prevent dental problems (z_6)
b20	0.09	**−0.31**	**−0.38**	**0.37**	**−0.23**	−0.08
b21	−0.02	**−0.19**	**−0.05**	**0.47**	0.01	−0.06

Note. Estimates in bold have more than 95% of their posterior mass away from zero.

Table 11 Unmet Demand Because of Price, Ingredients, Packaging, Interests, and Maintenance

a/b	Strong tasting (z_1)	Scratch enamel (z_2)	Irritate my mouth (z_3)	Cost too much (z_4)	Breath freshening doesn't last long (z_5)	Don't really work to prevent dental problems (z_6)
b22	**0.20**	**−0.14**	−0.04	**0.17**	**−0.12**	**−0.18**
b23	−0.03	0.10	**0.25**	**0.11**	**−0.14**	**−0.09**
b24	**−0.21**	−0.03	**0.24**	**−0.15**	−0.01	**−0.24**
b25	**0.20**	**−0.16**	0.02	**−0.24**	0.04	**−0.39**
b26	**−0.15**	**−0.14**	−0.10	**−0.31**	**0.11**	**0.18**
b27	0.09	0.01	**0.13**	**−0.13**	−0.06	−0.01
b28	−0.09	**0.10**	**0.25**	**−0.26**	**0.21**	−0.01
b29	**0.23**	0.01	**−0.23**	**0.43**	0.00	**0.37**
b30	−0.11	0.00	**0.17**	−0.05	**0.21**	0.04

Note. Estimates in bold have more than 95% of their posterior mass away from zero.

Table 12 Summary of Findings

People who believe...	have depressed demand for... (unmet demand)	and enhanced demand for... (met demand)
z_1: Toothpastes are too strong tasting.	Medical benefits, taste	Abrasiveness
z_2: Toothpastes scratch the enamel on my teeth.		Medical benefits, abrasiveness
z_3: Toothpastes irritate my mouth.	Medical benefits	Resulting appearance
z_4: Toothpastes cost too much.		Resulting breath
z_5: Toothpaste breath freshening doesn't last long enough.		Taste
z_6: Toothpastes don't really work to prevent dental problems.	Medical benefits, taste	Abrasiveness, resulting appearance

Stain removal is the most preferred a/b for respondents who feel toothpastes are too strong tasting (z_1) or that toothpastes do not really work to prevent dental problems (z_6). Whitening is also preferred among these respondents, as is the pearly whitening benefit. These same respondents, who do not believe in the ability of toothpaste to prevent dental problems (z_6), were described in Table 6 as not valuing enhancements in the medical benefits of toothpaste. They appear to have given up on receiving medical benefits and taste, and they instead seek toothpastes that are nonabrasive and deliver enhanced levels of appearance.

Table 10 displays the covariate relationship for the breath-freshening component. Levels of unmet demand are associated with beliefs about toothpaste scratching enamel (z_2), irritating one's mouth (z_3), and breath freshening not lasting long (z_5) for the enhanced a/b of 12-hour breath freshening (b20) and morning mouth (b21). Respondents who believe that toothpastes cost too much (z_4) prefer the morning-mouth benefit (b21) and also prefer the 12-hour breath-freshening benefit (b20).

Finally, Table 11 displays the covariate relationship for price, ingredients, and other components. Unmet demand is expressed as people being more price sensitive if they feel toothpastes do not work (z_6). Unmet demand for people who believe that ingredients are 100% natural (b23) exists in their lack of belief of long-lasting breath freshening (z_5). Similarly, we find unmet demand for packaging, social interests, and routine maintenance benefits (b24–b30).

A summary of the findings is presented in Table 12. We find that beliefs about toothpastes being too strong tasting (z_1) are associated with depressed demand for medical benefits and taste, and with heightened demand for toothpastes that are less abrasive. The belief that toothpastes scratch tooth enamel (z_2) is held by respondents with heightened demand for medical benefits and less abrasion. Respondents who believe that toothpastes irritate the mouth (z_3) have depressed demand for medical benefits and heightened demand for appearance attributes. Respondents who believe that toothpastes cost too much (z_4) have heightened demand for breath freshening, and those who believe that toothpaste breath freshening does not last long enough (z_5) have heightened demand for taste attributes. Finally, respondents who feel that toothpastes do not work to prevent dental problems (z_6) have depressed demand for medical and taste benefits but have heightened demand for abrasiveness and appearance attributes.

The predicted effects of changing consumer beliefs are a function of the coefficient matrix Γ and also the variable selection probabilities $\theta_{j,k}$. As reported in Table 5, the variable selection probabilities range from 0.73 for attribute b18 (makes your teeth gleam like pearls) to 0.12 for attribute b12 (doesn't irritate your mouth). These probabilities reflect the proportion of respondents in the responsive segment expected to experience change in demand as beliefs change. The identification of profitable campaigns to change respondents' beliefs of products in the product category requires knowledge of both parameters.

6. Concluding Remarks

In this paper we propose a model of heterogeneity useful for detecting unmet demand, which is defined as the presence of an underlying need not being fulfilled by the array of marketplace offerings. We assume that consumer value for the attributes and benefits of product offerings reflects met demand, which may be depressed or dampened by beliefs that products are costly to use or are ineffective. Here, we interpret cost in a broad sense to include factors that give rise to displeasure in use, including prices. Our inference about unmet demand is made through a cross-sectional analysis relating part-worth estimates in a conjoint analysis to beliefs about the performance of offerings in a product category.

A challenge in detecting unmet demand is in separating out respondents who have no demand for the attributes and benefits of a product. It is not possible to make an inference about unmet demand unless there is some positive demand present; however, much of it may be depressed. We propose a new model of heterogeneity that combines the heterogeneous variable selection model of Gilbride et al. (2006) with a normal component mixture model (see Rossi et al. 2005), which includes covariates, into the same model structure.

Our model of heterogeneity has two features useful for detecting unmet demand. First, the variable selection aspect of the model leads to a shrinkage value of zero rather than the mean of the mixing distribution. Unless there is information in the data likelihood that indicates otherwise, this distribution of heterogeneity assumes that demand for a product feature is zero. Second, the model allows for a potentially different covariate relationship to exist for each of the normal components. This offers the potential of identifying distinct response segments whose behavior is driven by different subsets of the model parameters, each with a unique relationship to the covariates. This could provide a richer description of heterogeneity that assumes a priori the existence of a common relationship.

In application to conjoint data of toothpaste, we find strong support for the proposed model. We detect the existence of a sizable response segment with very weak demand (i.e., part-worth estimates near zero) that negatively affects analysis relying on standard models of heterogeneity. We also find that only one additional response segment is required by the data and that the covariate relationship is homogeneous, not heterogeneous. Most surprisingly, we find that this best-fitting model explains the covariances detected with simpler models of heterogeneity. That is, covariances in the unobserved component of heterogeneity are nearly zero in the best-fitting model, indicating that our model is successful in explaining the structure of heterogeneity. Our analysis indicates that unobserved covariances are not due to a continuous preference relationship among respondents. Instead, they are driven by whether respondents have any nonzero preference for an attribute. This interpretation is confirmed by the large improvement in fit for the proposed model relative to simpler models (see Table 4).

We use the model to detect patterns of unmet demand using the coefficient matrix Γ that relates part-worth estimates to the beliefs about product offerings. The elements of the coefficient matrix are estimated to be large, with coefficient negative values pointing to patterns of unmet demand and positive values indicating where demand is being met by the attributes and their levels. As technology changes and brands are repositioned, the coefficients provide insight into which product attributes will be in greater demand as beliefs change. It also provides guidance as to which beliefs need to be addressed to increase demand for particular levels of an attribute.

We believe that our model of heterogeneity has application to a wide class of problems in marketing, wherever it is important to characterize relationships on "what is" as opposed to "what is not." Marketing research studies make wide use of screening questions to qualify respondents in surveys, and our model structure can be thought of as qualifying evidence for the measurement of associations by screening out the nonrespondents. In a needs-based market segmentation study, respondents are grouped into segments for characterization and further analysis. The basis for segment inclusion should, we believe, be focused on the common needs of respondents, not the common non-needs or needs that they do not have. In an analysis of price responsiveness, it does not make conceptual sense to include respondents who are not prospects in the product category and have no interest in making a purchase. Similar arguments can be made for studying response to changes in advertising and channel and product formulation, as well as for removing respondents from an analysis that provides random responses. Our model structure offers a device for controlling for such nonresponse.

There are numerous avenues for extending the analysis in this paper. In addition to offering a new model of heterogeneity that can be applied in other contexts, our analysis challenges conventional thinking about the presence of distinct segments in a population of respondents having distinct needs. We do not find a need for more than two normal components in the mixing distribution, with one reflecting the behavior of respondents who are disengaged from the study. Just one coefficient matrix, Γ, is found to be needed in our analysis. Moreover, the lack of heterogeneity covariances indicates a lack of response clusters in the distribution of heterogeneity. This challenges common notions of market segmentation where collections of need states give rise to distinct demand groupings. Additional research incorporating consumer needs into the analysis is desired, possibly using these variables to explain the process of variable selection.

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Appendix. Markov Chain Monte Carlo Estimation

The empirical application discussed in this article consists of 757 respondents filling out a conjoint survey of 30 toothpaste attributes and their levels. Ten sets of stimuli were presented with each set comprising of four hypothetical product offerings described by three attribute levels with respondents rank ordering these offerings. Let h denote the index of the respondent, let j denote the product offering, let m denote different sets of stimuli, and let k denote the number of latent segments.

Estimation is carried out by sequentially generating draws from the following distributions.

1. Generate β_h, τ_{hj} for $h = 1, \ldots, H$ respondents:
   The posterior for β_h is given by

$$\pi(\beta_h \mid \mu, \Sigma, \text{data}) \propto \mathrm{L}(\beta_h \mid \text{Data}) \times \pi(\beta_h \mid \Gamma' z_h, \varphi_k, \bar{\beta}_k, \Sigma_k), \quad (10)$$

where the likelihood, i.e., the first component of (1), is given by

$$\mathrm{L}(\beta_h \mid \text{Data}) = \prod_{m=1}^{10} \Pr(U_{1m} > U_{2m} > U_{3m} > U_{4m})_h = \prod_{m=1}^{10} \prod_{i=1}^{3} \frac{\exp(x'_{im}\beta_h)}{\sum_{j=i}^{4} \exp(x'_{jm}\beta_h)}.$$

The second component of (1),

$$\pi(\beta_h \mid \Gamma' z_h, \varphi_k, \bar{\beta}_k, \Sigma_k),$$

can be formulated as

$$\beta_h^* = C_{\tau h}^{-1} \beta_h \sim \Gamma' z_h + \sum_{k=1}^{K} \varphi_k \mathrm{N}(\bar{\beta}_k, \Sigma_k),$$

$C_{\tau h} = \mathrm{diag}(\tau_h)$, where $\tau_{hj} \sim \mathrm{Beta}(\theta_{jk})$ taking on values $(1, c)$.

The priors are specified as

$\tau_{hj} = 1$ with probability θ_{jk} and $\tau_{hj} = c$ with probability $1 - \theta_{jk}$,
$\bar{\beta}_k \sim \mathrm{Normal}(0, 100I)$,
$\Sigma_k \sim \mathrm{IW}(\nu, \Omega)$,
$\theta_{jk} \sim \mathrm{Beta}(a, b)$, with $a = b = 5$.

Draws of the conditional distribution are obtained with the Metropolis–Hastings algorithm with a random walk chain. The notation of (n) and (o) correspond to new and old draws.

(i) We set $\tau_{hj}^{(n)} = 1$ with a probability of θ_{jk}; else, $\tau_{hj}^{(n)} = c$ with a probability $1 - \theta_{jk}$.

(ii) $\beta_{hj}^{(n)}$ from $C_{\tau h}^{-1} \beta_h \sim \Gamma' z_h + \sum_{k=1}^{K} \varphi_k \mathrm{N}(\bar{\beta}_k, \Sigma_k)$.

(iii) The new values of $\tau_{hj}^{(n)}$ and $\beta_{hj}^{(n)}$ are accepted with a probability of

$$\Pr(\text{accept}) = \min\left[\frac{L_h(\beta_{hj}^{(n)}, \tau_{hj}^{(n)}) \times p(\beta_{hj}^{(n)}) \times p(\tau_{hj}^{(n)})}{L_h(\beta_{hj}^{(o)}, \tau_{hj}^{(o)}) \times p(\beta_{hj}^{(o)}) \times p(\tau_{hj}^{(o)})}, 1\right].$$

2. Generate $\bar{\beta}_k$: $\bar{\beta}_k \mid \{\beta_h^*\}, \{\tau_{hj}\}, \{\Gamma\}, \Sigma_k$:
   Form $\beta_h^* \sim C_{\tau h}^{-1} \beta_h$,

$$\bar{\beta}_k \sim \mathrm{Normal}\big(\tilde{\beta}, [(\Sigma_k/V)^{-1} + (100I)^{-1}]^{-1}\big),$$

$$\tilde{\beta} = \big[(\Sigma_k/V)^{-1} + (100I)^{-1}\big]^{-1} \left[\Sigma_k^{-1} \sum_{h=1}^{H} (\beta_h^* - \Gamma' z_h) + (100I)^{-1}\right].$$

3. Generate Σ_k: $\Sigma_k \mid \{\beta_h^*\}, \{\tau_{hj}\}, \{\Gamma\}, \bar{\beta}_k$:

$$\Sigma_k \sim \mathrm{IW}\left[\nu + V, \Omega + \sum_{h=1}^{H} (\beta_h^* - \Gamma' z_h - \bar{\beta}_k)'(\beta_h^* - \Gamma' z_h - \bar{\beta}_k)\right],$$

where IW is the inverted Wishart distribution with $\nu = J + 3$ and $\Omega = \nu I$.

4. Generate θ_{jk}: $\theta_{jk} \mid \tau_{hj}$:
   If $\tau_{hj} = 1$, then $q_{hj} = 1$; else, $q_{hj} = 0$.

$$\theta_{jk} \sim \mathrm{Beta}\left(a + \sum_{h=1}^{H} q_{hj}, V - \sum_{h=1}^{H} q_{hj} + b\right).$$

5. Generate Γ:

$$\pi(\Gamma \mid \{\beta_h\}, \Sigma) = \mathrm{Normal}(\hat{\Gamma}^*, \Sigma_{\hat{\Gamma}^*}), \text{ where}$$
$$\hat{\Gamma}^* = (Z'Z \otimes \Sigma^{-1} + (0.01)I)^{-1}(Z' \otimes \Sigma^{-1})B^*,$$
$$B^* = \mathrm{vec}(B) \text{ where } B = [\beta_1 \beta_2 \cdots \beta_H],$$
$$\Sigma_{\hat{\Gamma}^*} = (Z'Z \otimes \Sigma^{-1} + (0.01)I)^{-1},$$

and $(0.01I)$ is due to the prior on Γ: $\pi(\Gamma) = \mathrm{Normal}(0, 0.01I)$.

6. Generate latent indicator variable s_h and segment weights φ_k:

When making assignments of individuals to the components, we employ the standard procedure of augmenting the parameter space with a latent indicator variable s_h, which aids in determining to which of the components a respondent is associated. The draw for the latent variable s_h is done from

$$[s_h = k \mid \beta_h, C_{h,k}, \Gamma_k, \Sigma_k, \theta_k, \varphi_k] \propto \mathrm{Normal}(C_{h,k}^{-1} \beta_h \mid \Gamma'_k z_h, \Sigma_k) \times \varphi_k \times \prod_{j=1}^{J} \mathrm{Beta}(C_{j,k} \mid \theta_{j,k}).$$

The last factor on the right-hand side is the product of the probabilities associated with a respondent's $C_{\tau h}$.

The segment weights φ_k have Dirichlet distribution and are given by

$$[\varphi_k \mid s_h, k] \sim \mathrm{D}(\rho_1 + n_1, \rho_2 + n_2, \ldots, \rho_K + n_K),$$

where $n_k = \#\{i: s_i = k\}$ is the number of subjects assigned to segment k. In our analysis, we set $\rho_1 = \rho_1 = \cdots = \rho_K = 3$; given the large sample size for the data used, this prior specification results in a very mild influence on the posterior.

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