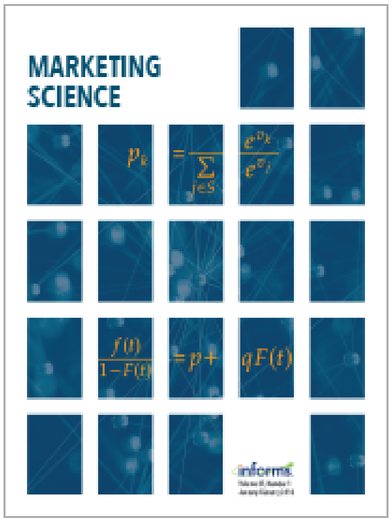

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# Modeling Variation in Brand Preference: The Roles of Objective Environment and Motivating Conditions

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## Abstract

People consume products in a variety of environments. They drink beer, for example, by themselves, with close friends, on the beach, when playing cards, at tailgate parties, and while having dinner with their boss. Within these environments, an individual may prefer Schaefer beer when drinking alone, Budweiser when having a party, Corona when lying on the beach, and Heineken when dining out. Preferences change across environments because the benefits sought by the consumer change. Consumers may feel thirsty while lying on the beach, and they may want to display refined tastes while dining out. Moreover, the effect of environment may not be homogeneous, as some people enjoy meeting new people in social gatherings while others may prefer to visit with those who are more familiar. Even though consumers face the same objective environment, different motivating conditions and brand preferences may arise.

It is important for marketing managers to understand how brand preferences change across people, environments, and motivating conditions and, more importantly, which product attributes are associated with these changes. Communication and positioning decisions are more likely to be effective if the relationships among objective environment, motivating conditions, and preferences for brand attributes are known. If motivating conditions are uniquely associated with individuals across environments, or with environments across individuals, then the basis of marketing analysis is at the individual or environmental level. If, however, motivating conditions arise from the intersection of individuals and their environments, then analysis conducted at the individual or environmental level will be insufficient to understand human behavior. In such a case, firms may want to view different environments as distinct markets, each with its own pattern of heterogeneous wants and competitive environment.

In this paper, the influence of objective environments and motivating conditions on brand preference is investigated. The mathematical model is based on the economic framework of utility maximization and discrete choice, and it accommodates three challenges that arise in modeling variation in brand preference. First, consumer consideration sets and purchase histories can vary widely across individuals in a relevant universe. Because brand preferences are the dependent variables in our analysis, our method must be able to accommodate a large number of brands to avoid restricting its measured variation as the objective environment and motivating conditions change. We propose a method using partial ranking data, combined with pairwise trade-off data, to obtain estimates of brand preference for all brands in our study. Second, the model must allow for multiple effects, leading to both within-person and across-person heterogeneity in preferences. Variation in brand preference is investigated within a hierarchical Bayes model in which motivating conditions are related to brand preference through a regression model in the random effects specification. Third, it is often counterintuitive for respondents to express preferences for attribute combinations that do not actually exist. A statistical method model is proposed for decomposing aggregate brand preferences into preferences for core and extended product attributes.

Data are collected from a national survey of consumer off-premises beer consumption. A total of 842 respondents from six different geographic markets participated. Data include preferred brand sets under different objective environments, brand choice rankings, product attributes, and motivating conditions. Effect sizes for respondent and objective environment are both large. We found that the level of explained variance in brand and attribute preference attributable to motivating conditions is greater than that accounted for by a simple interaction of respondent and environmental effects, suggesting that motivations provide a more sensitive description of variation in brand preference. Our findings indicate that 1) across individuals the objective environment is associated with heterogeneous, not homogeneous, motivating conditions; 2) within an individual, motivating conditions may change with variation in the objective environment; and 3) motivating conditions are related to preferences for specific attributes.

Our results imply that the unit of analysis for marketing is properly a person-activity occasion. Brands, for example, are used in individual instances of behavior—a brand performs well or poorly on individual occasions of use. The relevant universe is enumerated in person-activity occasions rather than in respondents. For some activities, such as doing the laundry, the occasions may typically occur in relatively unchanging environments, and it may be appropriate to allow respondents to summarize over occasions of the activity. For other activities, such as snacking or drinking beer, the activity may occur in distinct kinds of environment. In the case of such activities, it is appropriate to allow for the effect of changing environments to manifest themselves, if present. Doing so may require sampling from the relevant universe of person-activity occasions over an appropriate time frame. The design must be such as to record intraindividual variability due to changes in the environment for action.

(*Extended Choice Models; Hierarchical Bayes; Unit of Analysis*)

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## 1. Introduction

Human action involves an individual making an environmental impact of some sort. We drink beer; prepare, serve, and eat sitdown meals; get stains out of soiled laundry; put food in front of the dog; bring our car to the repair shop; choose a graduate school; all to adjust our relationship with our environment and improve our state of being. For some people, drinking a beer while working around the house may be different from drinking a beer at a party because the objective environment is different. While working around the house, we may be taking a break from a strenuous activity to quench our thirst, while at a party we may drink to relax and fit into the crowd. As the environment changes, motivating conditions (e.g., thirst, concern regarding social acceptance) and desired product attributes may change.

The purpose of this paper is to investigate the respective roles of objective environment and motivating conditions on brand preference. The objective environment comprises aspects of the setting in which activity takes place that can be publicly verified. If a given type of objective environment implies homogeneous motivating conditions (e.g., everyone drinking beer at a party is seeking social acceptance), then firms may regard the type of environment as sufficient for managerial action. If, however, motivating conditions are heterogeneous within the objective environment, then knowing the type of environment is insufficient for understanding human action. Moreover, if the motivating conditions and brand preference for an individual change across environments, then firms may want to view the different environments as distinct markets in which they face materially distinct competition.

Since the early discussions of market segmentation, marketers have tried to describe heterogeneity within product markets (e.g., Smith 1956). Some authors have included "situational" variables, operationalized as variation in activity, or in type of objective environment for activity (e.g., Belk 1975, Ratneshwar and Shocker 1991, Miller and Ginter 1979, Dickson 1982). However, this stream of research has not investigated the possible presence of heterogeneous motivating conditions within types of objectively described environments. Another stream of research has documented intraindividual variation in brand preference (McAlister and Pessemier 1982, McAlister 1982, Kahn et al. 1986, Allenby and Lenk 1994, Erdem 1996, Yang and Allenby 2000) due to variety seeking, carryover, state dependence, and variables such as price, but little is understood about the role played by the objective environment and motivating conditions. As McFadden (1986) notes, since econometric models based on "revealed market data" (p. 275) are inadequate in describing the underlying mechanisms that govern behavior, it is important to make use of psychometric data to help better understand and predict consumer behavior.

**Figure 1** **A Model for Explaining Variation in Brand Preference (Adapted from Fennell 1988)**

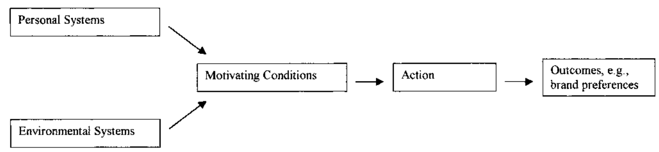



Figure 1 displays an abbreviated model of brand preference used in this study that focuses attention on variables of interest. Personal and environmental systems intersect to allocate an individual's resources to a domain of action and direction of desired adjustment within that domain. For example, an individual's metabolic and psychological systems can be thought to intersect with the heat, humidity, and weight of objects while working around the house. The outcome is motivating conditions (e.g., thirst, boredom, tiredness, concern about feeling bloated) that specify the kinds of attribute an individual finds valuable, i.e., worth using resources to search for and exchange resources for the right to use, as one tries to effect an adjustment in hope/expectation of improving one's state of being. Beliefs/knowledge of the attributes of brands is the means by which resources are further directed to find brands that are responsive to motivating conditions as experienced by the individual. Figure 1 is abbreviated in that it does not include variables such as perceptions, beliefs, and search that are present in extended models of behavior (e.g., Ben-Akiva et al. 1999, Fennell 1988, McFadden 1986, Howard and Sheth 1969).

Motivation is operationalized here as concerns and interests relevant to an activity (Fennell 1988, 1997). We note that our use of the word ''motivation'' refers to a qualitative variable that selects a domain (air temperature adjacent to the skin) and direction of adjustment (e.g., more/less) believed likely to improve one's state of being. In contrast to the term ''motive,'' which refers to a trait-like variable, i.e., intended to apply across activity and over time (e.g., high/low in stick-to-it-iveness), motivation refers to a variable whose scope is appropriate to a single occasion of an activity, ''I ache, feel parched, dusty, and sweaty.'' We reject ''motive'' for our purposes because the scope of a trait-like term is unnecessarily broad in the context of marketing where goods/services are developed and supported, one at a time, each within its own substantive and competitive universe. Moreover, learning that an individual is ''high/low in stick-to-it-iveness'' lacks the crucial domain-relevant content (e.g., in regard to working around the house) needed to give managerial direction to product policy for a specific offering.

We use an econometric model of brand preference for studying the role of objective environment and motivating conditions. A challenge in calibrating estimates of brand preference is the large number of brands that exist in most product categories, for which consumers have well-defined preferences for a small subset. We propose a method of combining partial ranking data on all brands, with detailed preference data on some of the most preferred brands, to yield estimates of brand preference for all brands in category. This method allows us to study variation in brand preference without overly constraining the number of brands in an analysis.

Respondent effects, environmental effects, and motivating conditions enter the model specification through the distribution of heterogeneity that allows for inter- and intraindividual variation in brand preference. Brand preferences are related to motivating conditions through a regression model in a random-effects specification. A method of projecting the coefficients of this relationship onto the subspace of core and extended product attributes is proposed, resulting in estimates of the relationship between motivating conditions and attribute preference. Our results indicate that (1) across individuals the objective environment is associated with heterogeneous, not homogeneous, motivating conditions; (2) within an individual, motivating conditions change with variation in the objective environment; and (3) motivating conditions are related to preferences for specific attributes.

The remainder of the paper is organized as follows. Section 2 describes a survey-based approach to obtaining brand preferences when a large number of brands are present in a product category, and a statistical model for relating brand preferences to respondent effects, environment-type effects and motivating conditions. Alternative models are proposed to investigate the explanatory contributions of these variables to brand preference. Section 3 describes the method of data collection, and §4 summarizes characteristics of the data from a proprietary national survey of consumer beer drinking. Results are reported in §5 and implications are discussed in §6. Section 7 offers concluding comments.

## 2. A Model for Inter- and Intrapersonal Variation in Brand Preference

Three challenges arise in modeling effects associated with brand preference. First, consumer consideration sets and purchase histories can vary widely across individuals in a population. Since brand preferences are the dependent variables in our analysis, our method must be able to accommodate a large number of brands to avoid restricting its measured variation as the objective environment and motivating conditions change. Second, the model must allow for multiple effects, leading to both within-person and across-person heterogeneity in brand preference. Third, it is often counterintuitive for respondents to express preferences for attribute combinations that do not actually exist. A statistical method model is therefore needed to study the influence of objective environment and motivating conditions on attribute-level importance (i.e., part-worths).

Our model for studying the source of brand preference is embedded within a hierarchical Bayes structure (see Allenby and Rossi 1999). In a hierarchical structure, the model for the variation in brand preferences (i.e., the heterogeneity distribution) can be considered independently from that portion of the model that yields an estimate of brand preference (i.e., the likelihood). The likelihood function relates the observed data to the latent brand preference. The distribution of heterogeneity describes how these preferences vary as a function of respondent effects, environmental effects, and motivating conditions. In the following discussion we first examine how brand preferences can be obtained in settings where there exist many brands, and consumers are assumed to be able to provide meaningful choices only within a small subset. We then describe our model for the distribution of heterogeneity and our method of estimating the association between motivating conditions and product attributes.

**The Likelihood**

Assume there are $J$ brands in a product category. We assume that a respondent can identify a subset of $j$ brands that he/she would consider using in a particular environment and that these brands have higher utility, discounted by average price, than the brands not included in the consideration set:

$$(u_1/\bar{p}_1, \ldots, u_j/\bar{p}_j) > (u_{j+1}/\bar{p}_{j+1}, \ldots, u_J/\bar{p}_J), \quad (1)$$

where $u_j$ indicates the marginal utility of brand $j$ and $\bar{p}_j$ is its average price. We suppress indices for individual, environmental, and motivational effects until we introduce our model of heterogeneity.

The identification of the consideration set leads to a partial ranking of the alternatives. A partial ranking differs from a standard choice outcome in that it identifies one or more alternatives as more preferred to another set of other alternatives. Computing the probability of the partial ranking is difficult because of the many overlapping regions of the errors that must be considered. For example, the probability of the partial ranking $(r, s) > (t)$ is not equal to $\Pr(r > t) + \Pr(s > t)$ unless $\{r\}$ and $\{s\}$ are disjoint. While it is possible to avoid computation of partial ranking probabilities by introducing latent variables (see McCulloch and Rossi 1994 for application to probit models), it is desirable to be able to evaluate the likelihood for model testing purposes. Assuming that log marginal utility is stochastic with extreme value error, the contribution to the likelihood of the consideration set can be expressed as (see Ophem et al. 1999):

$$g = \Pr\{(u_1/\bar{p}_1, \ldots, u_j/\bar{p}_j) > (u_{j+1}/\bar{p}_{j+1}, \ldots, u_J/\bar{p}_J)\}$$

$$= 1 + \sum_{k=1}^{j} (-1)^k \Phi_{(1,j)}^{(k)}, \quad (2)$$

$$\Phi_{(1,j)}^{(k)} = \sum_{l_1=1}^{j} \sum_{l_2=l_1+1}^{j} \cdots \sum_{l_k=l_{k-1}+1}^{j} \times \frac{W_J}{\exp(V_{l_1} + \cdots + \exp(V_{l_k}) + W_J}, \quad (3)$$

$$W_J = \sum_{l=j+1}^{J} \exp(V_l), \quad (4)$$

$$V_l = \beta_l + \beta_p \ln \bar{p}_l, \quad (5)$$

where $\beta_l$ is a measure of brand preference and $\beta_p$ is the price coefficient. Equation (2) writes the probability in terms of the complement set, and Equation (3) is needed so that overlapping regions in the calculation are not double counted. Consider the case when $j = 2$ and $J = 3$, or $g = \Pr(\{u_1/\bar{p}_1, u_2/\bar{p}_2\} > u_3/\bar{p}_3) = 1 - \Pr(u_3/\bar{p}_3 > u_1/\bar{p}_1 \text{ or } u_2/\bar{p}_2) = 1 - \Pr(u_3/\bar{p}_3 > u_1/\bar{p}_1) - \Pr(u_3/\bar{p}_3 > u_2/\bar{p}_2) + \Pr(u_3/\bar{p}_3 > \max\{u_1/\bar{p}_1, u_2/\bar{p}_2\})$. Equation (2) sets $g = 1 - \Phi_{1,2}^1 + \Phi_{1,2}^2$, and from Equation (3) we have $\Phi_{1,2}^1 = \exp(V_3)/[\exp(V_1) + \exp(V_3)] + \exp(V_3)/[\exp(V_2) + \exp(V_3)]$, and $\Phi_{1,2}^2 = \exp(V_3)/[\exp(V_1) + \exp(V_2) + \exp(V_3)]$, leading to a closed-form expression for the partial ordering: $g = 1 - \Pr(u_3/\bar{p}_3 > u_1/\bar{p}_1) - \Pr(u_3/\bar{p}_3 > u_2/\bar{p}_2) + \Pr(u_3/\bar{p}_3 > \max\{u_1/\bar{p}_1, u_2/\bar{p}_2\})$.

Given the identification of brands in the considered set, we propose using a series of simple conjoint exercises among the subset brands and prices to obtain more precise information about preference. Information can be efficiently obtained using full rankings for the considered brands and their associated prices. For each set of profiles in the series, the contribution to the likelihood for the full ranking is easily obtained using the exploding technique of Chapman and Staelin (1982):

$$p_n = \Pr(u_1/p_1 > u_2/p_2 > \cdots > u_j/p_j)$$

$$= \prod_{k=1}^{j-1} \Pr(u_k/p_k > u_m/p_m,\ m = k + 1, \ldots, j), \quad (6)$$

$$\Pr(u_k/p_k > u_m/p_m,\ m = k + 1, \ldots, j)$$

$$= \frac{\exp(\beta_k + \beta_p \ln p_k)}{\sum_{l=k}^{j} \exp(\beta_l + \beta_p \ln p_l)}, \quad (7)$$

where the price coefficient $\beta_p$ is the inverse of the scale value of the random utility error. We note that the vector of brand preferences, $\beta$ in Equation (7), is composed of $J - 1$ brand elements plus one price coefficient.

The likelihood makes effective use of properties of the extreme value error. This error term simplifies the computation of the likelihood for both the partial ranking—Equation (1)–(5)—and the full ranking of a subset of items in the consideration set—Equation (6)–(7). The extreme value error is also associated with the well-known IIA (Independence of Irrelevant Alternative) property. We use this property in Equations (6) and (7) by assuming that the choice probabilities are not a function of the brands outside the consideration set. The IIA property allows us to gather detailed preference information about a subset of brands through a series of conjoint tasks independent of the other brands present in the product category.

The likelihood for an individual set of responses is the product of partial ranking (of all brands) probability and the probabilities associated with the series of full rankings of a subset of most preferred brands in the conjoint exercise. We assume that the vector of errors is independent in these components, resulting in a likelihood of the form:

$$l(\beta) = g \times \prod_n p_n, \quad (8)$$

where $g$ is the partial rank probability (Equation (2)) and $p_n$ is the full rank probability for the $n$th set of conjoint profiles (Equation (6)).

Our assumption of the independence of the error terms across the $n$ conjoint-ranking tasks and the initial partial ranking of all brands leads to a tractable likelihood function that can accommodate a large number of brands. We emphasize that this assumption is made conditional on the model parameters $\beta$ whose heterogeneity distribution is discussed below. While the assumption of independent conditional errors is commonly made in conjoint studies and applied demand analysis, it can lead to misspecifications, particularly when there exist sources of dependencies such as learning effects and state dependence that may induce some form of serial correlation in the data (see Allenby and Lenk 1994, Haaijer et al. 1998). We note that the assumption of a common error term (i.e., one draw, not $n$ independent draws) across the conjoint profiles is not supported in our data—roughly 20% of the respondents exhibit some form of observation error where a brand is reported to be ranked higher than an alternative in one profile, yet lower than the same alternative in another profile when prices are the same. The data therefore exhibit some respondent judgment error. The treatment of more complicated error structure is outside the scope of this paper, and we retain the independence assumption for tractability.

Another alternative to studying a large number of brands is to use availability designs as suggested by conjoint literature (Lazari and Anderson 1991, Anderson and Wiley 1992). This approach randomly assigns different subsets of brands to individuals and models the brand utility as a function of its own attributes, the attributes of the competing brands, and the availability of the competing brands. However, this is not an appropriate solution in our study for two reasons. First, an individual tends to have specific consideration sets within a consumption situation, which does not fit into the random assignment framework. Second, the large number of brands leads to a large number of subset combinations.

**Distribution of Heterogeneity**

The distribution of heterogeneity relates respondent effects, environmental effects, and motivating conditions to brand preference. The personal and environmental systems in Figure 1 are not parameterized in our study. Instead, we employ various forms of effects coding (described below) that identify survey respondents and selected environments without specifying the specific systems at work. This coding is consistent with the current heterogeneity literature employing both fixed-effect and random-effect specifications.

A simple model for studying variation in brand preference is to assume an additive model for respondent and environmental effects:

$$\beta_{re} = \nu_r + \nu_e, \tag{9}$$

where $\nu$ denotes an effect, $r$ denotes the respondent, and $e$ denotes the objective environment. Common random-effect models of sales data using hierarchical Bayes (Allenby and Rossi 1999) and finite mixture models (Kamakura and Russell 1989) have ignored the second component in Equation (9) and have specified that variation in brand preference is entirely driven by the respondent effect, $\nu_r$. This is largely due to the lack of information about the objective environment.

A second model for variation in brand preference is to assume that personal and environmental effects interact to produce unique brand preferences for each respondent-environment combination. For example, in social environments a person may be motivated to impress others and may prefer a set of brands that are different from those preferred in a nonsocial setting. If preferences are independent across respondents and environments, then the respondent-environment effect, $\nu_{re}$, is designated by both respondent and environmental subscripts. That is, the analysis is conducted with a base of person-activity occasions rather than respondents.

A third model for variation in brand preference is displayed in Figure 1, where personal and environmental systems intersect to produce motivating conditions. These conditions lead to actions and brand preference. For example, an individual donating money to a charity (the action and brand) may want to make amends for some past misdeeds, or may want to view him/herself as the "sort of person" who gives regularly to charity. The individual may donate regularly as a matter or routine (e.g., tithe), or may be interested in certain scientific issues that call for additional research. Moreover, the universe of donating occasions for an individual is diverse, involving a variety of objective environmental effects including the loss of a loved one, or receipt of an appeal via direct mail or media broadcast. Preference among candidate charitable organizations results from the prospective donor matching motivating conditions and perceptions of the organizations. A general model for capturing the influence of motivating conditions beyond that explained by respondent and environment effects is:

$$\beta_{re} = \nu_m + \nu_{re}, \tag{10}$$

where $m$ denotes motivation. If objective environments are associated with characteristic motivations, then motivating conditions are redundant and $\nu_m$ is not needed in the heterogeneity specification. If individuals are motivated similarly across environments, then environmental conditions are redundant and $\nu_{re}$ can be replaced with $\nu_r$.

Fixed and random effects are used to model the influence of respondent and environmental effects and motivating conditions. Fixed effects are employed when there exist sufficient data to reliably estimate effect coefficients, and random effects are used when data are sparse and pooling assumptions are required. In the analysis presented below, fixed effects are modeled via a regression function $\nu = \Lambda z$ where $z$ is a vector of covariates, and random effects are modeled with a multivariate normal distribution $\nu \sim \text{Normal}(\mu, \Sigma)$. We note that it is possible to include regressors in the random-effect specification by relating them to the mean of the distribution, i.e., $\mu = \Lambda z$ (cf. Allenby and Ginter 1995, Rossi et al. 1996), so the fixed-effect specification can be seen as a nested case of the random-effect model.

**Obtaining Attribute Part-Worth Associations**

The $(i, j)$ element of $\Lambda$ describes the degree to which variation in preference for brand $i$ is related to the $j$th covariate in the vector $z$. The covariate $z_m$, motivating conditions, however, refers to both what an individual lacks and the kind of attributes that will supply what is lacking, which the individual is ready to spend resource to acquire. To get from wants to brand preference requires that individuals know the claimed attributes of some brands, and judge them likely to supply what is lacking. It is therefore of interest to investigate the association between the brand effects in $\Lambda$ and the effects of specific attributes. This can be accomplished by projecting the coefficients in $\Lambda$ onto the subspace defined by the column vectors of an attribute matrix $A$ for the brands:

$$\Lambda = A\Gamma + \Pi, \tag{11}$$

where $\Gamma$ is a matrix of attribute coefficients and $\Pi$ is a matrix of residual values.

The projection is identical to that encountered in standard regression analysis. For example, if the matrix of coefficients were directly observed, one could consider using a least-squares procedure to obtain estimates of $\Gamma$ by regressing $\Lambda$ onto $A$. For $A$ composed of a single-column vector describing a specific set of brand attribute levels, $\Gamma$ becomes a row vector with coefficients that are the least-squares projection of $j$th column of $\Lambda$ onto $A$. The $k$th element of the row vector $\Gamma$ reflects the change in the importance of the attribute for a unit change in the $k$th component of $z$. Combining (10) and (11), and assuming a random effects for $\nu_{re}$ and fixed effects for $\nu_m$, we obtain:

$$\beta_{re} = \Lambda z_m + \nu_{re} \tag{12}$$

$$= (A\Gamma + \Pi)z_m + \nu_{re}, \qquad \nu_{re} \sim \text{Normal}(0, \Sigma), \tag{13}$$

where $z_m$ is the vector of covariates describing the motivating conditions (see below), and the degradation in fit due to the projection of $\Lambda$ onto $A$ is reflected in the matrix of residuals $\Pi$. In our empirical analysis we compare the model fit using (12) to a constrained version of (13) that ignores the residual matrix:

$$\beta_{re} = A\Gamma z_m + \nu_{re}, \qquad \nu_{re} \sim \text{Normal}(0, \Sigma). \tag{14}$$

The column dimension of the matrix $A$ in Equation (12) is lower than that of the brand preferences vector $\beta_{re}$. If $A$ is composed of attributes that are capable of accurately reflecting variation in brand preference, then $\Pi$ will be small and there will be minimal degradation in model fit. A specification test for the sufficiency of the attributes in describing variation in brand preference therefore involves a comparison of model fit between Equations (12) and (14).

**Table 1 Sample Composition (Geographic Region and Demographics)**

| Region | Sample Size | Percent |
|---|---|---|
| North Carolina | 111 | 14 |
| Illinois | 120 | 14 |
| Ohio | 120 | 14 |
| Texas | 120 | 14 |
| Florida | 120 | 14 |
| California | 251 | 30 |
| **Age** | **N** | **Percent** |
| 21–27 | 214 | 25 |
| 28–34 | 207 | 25 |
| 35–50 | 421 | 50 |
| **Gender** | **N** | **Percent** |
| Male | 631 | 75 |
| Female | 211 | 25 |

## 3. Method

The data were collected by the Consumer Insights Group at the Miller Brewing Company, a major U.S. beer producer. Their knowledge about the product category provided guidance to, and informal validation of, our empirical study. The collaboration provided an opportunity to customize the design of an existing study and allow for the inclusion of motivational variables. Beer is a good consumed by many individuals in many objective environments, providing an opportunity to examine the influence of objective environment and motivating conditions on brand preference.

Respondents were recruited to the study through mall intercepts from geographically dispersed markets in California, Florida, Illinois, North Carolina, Ohio, and Texas. Table 1 reports the sample composition of the 842 respondents who participated. Respondents were qualified to reflect characteristics of moderate to heavy beer drinkers—consumption of at least six 12 oz. bottles of beer per week and age between 21 and 50. The ratio of male–female is three to one in our sample. The median weekly beer consumption is nine bottles (12 oz.) and the median weekly beer expenditure is 15 dollars.

Respondents were first queried on how often (e.g., sometimes, rarely, or never) they drank beer in various objective environments (see Table 2). Each re-

**Table 2 Objective Environments: Off-Premise Beer-Drinking Occasions and Their Frequency in the Sample**

| Home/Alone (22%) | Home/With Others (40%) | Away from Home/ With Others (38%) |
|---|---|---|
| (c1) Watching sports on TV by yourself/with household members (5.0%) | (c6) Dinner/barbecue with friends at your home (9.1%) | (c12) Party at a friend's house with a large group of people (12.5%) |
| (c2) Watching TV shows (not sports) or videos by yourself/with household members (4.4%) | (c7) Family gatherings at your home (5.1%) | (c13) At a friend's house with small group of people (8.2%) |
| (c3) Dinner by yourself or with household members (3.9%) | (c8) Party at home with friends (10.3%) | (c14) Outdoors at park, beach, tailgate, picnic (5.9%) |
| (c4) Working around the house (3.9%) | (c9) Watching sports on TV at home with friends (5.7%) | (c15) Outdoors hiking, camping, hunting, fishing (4.2%) |
| (c5) Relaxing at home (not watching TV) by yourself with household members (5.0%) | (c10) Watching TV shows (not sports) or videos with friends at your home (4.0%) | (c16) Playing or watching sports where you bring the beer (7.1%) |
| | (c11) Relaxing at home with friends (5.5%) | |

spondent was then assigned to two environments that they encountered in their daily lives. The environments fall into three categories: at home/nonsocial, at home/social, and out-of-home/social. For each environment the respondent reported the brands they would consider using, providing the partial ordering of the brands in Equation (1). In addition to the partial ordering data, respondents provided a full ranking for a series of six conjoint exercises involving five of their most preferred brands at various prices (see Equation (6)). Table 3 provides a list of the brands included in the study.

For each of two objective environments, respondents also reported, on one to five point scales, their agreement with a series of statements descriptive of their concerns and interests (see Table 4). The statements are based on information provided by the Miller Brewing Company and are loosely modeled on each of the seven motivational classes discussed by Fennell (1997).

## 4. Data

For each of the 842 respondents in each of two objective environments, the data comprise: (i) identification of the brands from Table 3 that would be considered for use (see Equation (1)); (ii) six sets of complete rankings of five brands from the consideration set under different prices (see Equation (6)); and (iii) data on agreement with a series of motivational statements (Table 4). A simple analysis of the data reveals evidence that the objective environment is not associated with characteristic motivations—that is, respondents within an environment type do not report the same kind of motivating condition. Table 5 reports the proportion of respondents in each environment who indicated that the descriptive statement of motivation pertains to them. If characteristic motivations were present, then the proportion would be large for some environments

**Table 3 Brand Names**

| | | |
|---|---|---|
| Beck's | Keystone Light | Natural Light |
| Bud Ice | Lowenbrau Special | Old Milwaukee |
| Bud Light | Michelob | Old Style |
| Budweiser | Michelob Golden Draft | Pabst Blue Ribbon |
| Busch | Michelob Light | Red Dog |
| Busch Light | Mickey's Malt Liquor | Samuel Adams Boston Lager |
| Coors Light | Miller Genuine Draft | Schlitz Malt Liquor |
| Coors Original | Miller Genuine Draft Light | Shiner Bock |
| Corona Extra | Miller High Life | Sierra Nevada Pale Ale |
| Heineken | Miller Lite | Tecate |
| Icehouse | Natural Ice | Weinhard's Ale |

**Table 4 Concerns and Interests Relevant to Consuming Beer**

| | |
|---|---|
| m1 | I was thirsty |
| m2 | I felt stressed and wanted to relax |
| m3 | I was proud of my refined tastes in beer |
| m4 | I enjoyed being part of the crowd |
| m5 | I enjoyed drinking a cool brand of beer |
| m6 | I didn't think much about which beer I was drinking |
| m7 | I was enjoying the taste, color, and the aroma of the beer |
| m8 | I wanted to read the label to see what was in the beer or where it was brewed |
| m9 | I liked drinking a popular beer |
| m10 | I wanted to meet new people |
| m11 | I didn't want to get too full on beer |
| m12 | I was happy that I got a good deal on the beer I bought |
| m13 | I was thinking about myself, my past, and my future |
| m14 | I was having a lot of fun |
| m15 | I was bored |
| m16 | I wanted other people to try the beer I was drinking |
| m17 | I was enjoying the way the beer went with food or snacks |

**Table 5 Proportion Reporting Concern/Interest "Always/Sometimes" for Each Objective Environment**

| | m1 | m2 | m3 | m4 | m5 | m6 | m7 | m8 | m9 | m10 | m11 | m12 | m13 | m14 | m15 | m16 | m17 | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| c1 | 0.44 | 0.21 | N/A | N/A | N/A | 0.25 | 0.53 | 0.12 | N/A | N/A | 0.29 | 0.31 | 0.16 | 0.58 | 0.06 | N/A | 0.52 | 0.32 |
| c2 | 0.45 | 0.34 | N/A | N/A | N/A | 0.23 | 0.55 | 0.23 | N/A | N/A | 0.20 | 0.45 | 0.16 | 0.53 | 0.11 | N/A | 0.50 | 0.34 |
| c3 | 0.56 | 0.39 | N/A | N/A | N/A | 0.33 | 0.64 | 0.32 | N/A | N/A | 0.33 | 0.42 | 0.33 | 0.47 | 0.20 | N/A | 0.67 | 0.42 |
| c4 | 0.61 | 0.30 | N/A | N/A | N/A | 0.26 | 0.62 | 0.14 | N/A | N/A | 0.36 | 0.44 | 0.26 | 0.35 | 0.15 | N/A | 0.39 | 0.35 |
| c5 | 0.42 | 0.40 | N/A | N/A | N/A | 0.25 | 0.48 | 0.20 | N/A | N/A | 0.29 | 0.38 | 0.31 | 0.41 | 0.21 | N/A | 0.51 | 0.35 |
| c6 | 0.45 | 0.34 | 0.38 | 0.45 | 0.37 | 0.27 | 0.58 | 0.22 | 0.40 | 0.29 | 0.32 | 0.49 | 0.19 | 0.73 | 0.13 | 0.32 | 0.53 | 0.38 |
| c7 | 0.44 | 0.30 | 0.44 | 0.40 | 0.45 | 0.34 | 0.59 | 0.21 | 0.40 | 0.16 | 0.34 | 0.34 | 0.16 | 0.65 | 0.12 | 0.27 | 0.50 | 0.36 |
| c8 | 0.42 | 0.26 | 0.35 | 0.49 | 0.44 | 0.26 | 0.56 | 0.20 | 0.39 | 0.31 | 0.32 | 0.48 | 0.18 | 0.77 | 0.09 | 0.33 | 0.52 | 0.37 |
| c9 | 0.26 | 0.16 | 0.31 | 0.31 | 0.49 | 0.23 | 0.52 | 0.16 | 0.41 | 0.18 | 0.28 | 0.39 | 0.14 | 0.68 | 0.07 | 0.25 | 0.39 | 0.31 |
| c10 | 0.35 | 0.37 | 0.34 | 0.28 | 0.51 | 0.16 | 0.60 | 0.22 | 0.46 | 0.26 | 0.38 | 0.51 | 0.25 | 0.57 | 0.13 | 0.26 | 0.47 | 0.36 |
| c11 | 0.41 | 0.29 | 0.31 | 0.39 | 0.38 | 0.11 | 0.47 | 0.23 | 0.33 | 0.24 | 0.26 | 0.33 | 0.29 | 0.60 | 0.08 | 0.19 | 0.44 | 0.31 |
| c12 | 0.47 | 0.30 | 0.31 | 0.49 | 0.37 | 0.30 | 0.50 | 0.16 | 0.37 | 0.37 | 0.30 | 0.40 | 0.18 | 0.72 | 0.10 | 0.25 | 0.46 | 0.36 |
| c13 | 0.43 | 0.28 | 0.33 | 0.50 | 0.39 | 0.20 | 0.46 | 0.22 | 0.33 | 0.34 | 0.33 | 0.43 | 0.24 | 0.72 | 0.08 | 0.17 | 0.49 | 0.35 |
| c14 | 0.45 | 0.27 | 0.34 | 0.35 | 0.45 | 0.31 | 0.52 | 0.30 | 0.37 | 0.30 | 0.25 | 0.46 | 0.16 | 0.71 | 0.09 | 0.26 | 0.47 | 0.36 |
| c15 | 0.54 | 0.28 | 0.41 | 0.44 | 0.42 | 0.30 | 0.59 | 0.20 | 0.41 | 0.32 | 0.32 | 0.44 | 0.21 | 0.70 | 0.11 | 0.34 | 0.55 | 0.39 |
| c16 | 0.44 | 0.29 | 0.38 | 0.39 | 0.49 | 0.28 | 0.48 | 0.23 | 0.42 | 0.25 | 0.32 | 0.38 | 0.14 | 0.67 | 0.15 | 0.27 | 0.45 | 0.35 |
| Mean | 0.45 | 0.30 | 0.35 | 0.41 | 0.43 | 0.26 | 0.54 | 0.21 | 0.39 | 0.27 | 0.31 | 0.42 | 0.22 | 0.62 | 0.12 | 0.26 | 0.49 | |

*Note:* c1–c16 indicates the 16 objective environments, and m1–m17 indicates the 17 motivating conditions. "NA" indicates that respondents did not have an opportunity to report this concern/interest for the objective environment indicated.

(i.e., near 1.0) and small in others. This pattern is not present in Table 5 as the proportions in any column of the table show a much more limited range.

In addition to the data obtained from the respondents, we employed two other pieces of information in our analysis. The first was the attribute matrix, $A$, described in Equation (11). This matrix was provided to us by the Miller Brewing Company and is reported in Table 6. The attributes include core product attributes reflecting the formulation of the offerings, and brand/trademark (e.g., Anheuser-Busch) dummy variables that attempt to capture extended attributes related to the psychological and sociological benefits of the brand. We also included an additional column vector in $A$ for the price coefficient. This column vector takes on values of zero everywhere except for one entry equal to one for the price coefficient. This allows us to project the relative brand preferences onto a lower-dimensional attribute space while retaining the original parameterization for the price coefficient.

**Table 6 Product Attributes**

| Variable Name | Variable Meaning | Coding Structure |
|---|---|---|
| A_P | Above Premium | Dummy |
| A-B | Anheuser-Busch | Dummy |
| B_P | Below Premium | Dummy |
| Bud | Bud | Dummy |
| Bud L | Bud Light | Dummy |
| Coors | Coors | Dummy |
| Coors L | Coors Light | Dummy |
| High Life | Miller High Life | Dummy |
| Ice | Ice beer/Malt liquor | Dummy |
| Import | Import beer | Dummy |
| Miller Genuine Draft | Miller Genuine Draft | Dummy |
| Michelob | Michelob | Dummy |
| Bitter | Bitter aroma | Expert rating 1–60 |
| Calories | Calories | True calorie content |
| Flavor | Sharp flavor | Expert rating 1–60 |
| Fruity | Fruity aroma | Expert rating 1–60 |
| Head | Appearance of the head | Expert rating 1–60 |
| Smooth | Smooth mouth-feel | Expert rating 1–60 |

The core product attributes were obtained from a panel of expert tasters employed by Miller. While it may be true that individual respondents' perceptions may vary from the perceptions of the expert tasters, the experts' ratings form an objective basis for predicting how changes in a brand's formulation will translate into changes in share in a particular objective environment. Respondent variation in perceptions creates an errors-in-variables problem that obscures the measurement of true respondent

**Table 7 Model Fit**

| Model | Description | | | Fixed Effect | Random Effect | Model Fit |
|---|---|---|---|---|---|---|
| 1 Baseline | $\beta_{re} = \bar{\beta}$ | | | None | None | −33050.96 |
| 2 Additive | $\beta_{re} = \nu_r + \nu_e$ | $\nu_e = \Lambda z_e$ | $\nu_r \sim \text{Normal}(0, \Sigma)$ | Environment | Respondent | −28448.17 |
| 3 Multiplicative | $\beta_{re} = \nu_{re}$ | $\nu_{re} \sim \text{Normal}(\mu, \Sigma)$ | | None | Respondent × Environment | −19872.72 |
| 4 Motivational | $\beta_{re} = \nu_m + \nu_{re}$ | $\nu_m = \Lambda z_m$ | $\nu_{re} \sim \text{Normal}(0, \Sigma)$ | Motivation | Respondent × Environment | −18410.70 |
| 5 Attribute | $\beta_{re} = \nu_m + \nu_{re}$ | $\nu_m = A\Gamma z_m$ | $\nu_{re} \sim \text{Normal}(0, \Sigma)$ | Motivation × Attribute | Respondent × Environment | −18240.46 |

*Note*: Fit is measured by the log marginal density calculated using the importance sampling method of Newton and Raftery (1994, p.21).

perceptions but does not affect predictive properties of the model (see Greene 1990).

The second piece of information employed in the analysis is the average price, $\bar{p}_j$, in the partial ordering in Equation (1). Twelve-pack regular prices were used as the average price, taking into account the geographic variation and availability. In cases where a brand was not offered in a particular region, we used a high price ($100) to ensure that the probability of consideration was near zero.

## 5. Results

Estimation was carried out using Markov chain Monte Carlo methods (see Gelfand and Smith 1990, Gelfand et al. 1990). Draws from the posterior distributions were used to evaluate means and standard deviations of the parameter estimates. The chain ran for 30,000 iterations and the last 5,000 iterations were used to obtain parameter estimates. Convergence was assessed by starting the chain from multiple points and inspecting time-series plots of model parameters. Estimation algorithms are provided in the Appendix.

### Model Comparison

Table 7 reports the fit statistics for six different models. The first model is an aggregate model that does not attempt to account for any variation in brand preference. The second model assumes an additive specification for personal and environmental conditions (Equation (9)). Objective environments are specified as fixed effects, and respondent effects are assumed to be random. Random effects are specified for the respondents because of the large number (842) present in the study. In contrast, there are only 16 different objective environments, making the fixed effects computationally feasible. The third model specifies a multiplicative relationship between respondents and objective environments, generating a new vector of coefficients for each respondent-environment combination $\nu_{re}$. The fourth model introduces motivating conditions, the concerns and interests that reflect the user's subjective experience of the context for consuming beer (Equation (12)). The fifth model relates motivating conditions to brand attributes, offering the chance to understand how variation in brand preferences is associated with core and extended attributes (Equation (14)).

The model fit statistics indicate the following. First, respondent and objective environment effects play a large role in explaining variation in brand preference. A comparison of the fit statistics for the first three models indicates that the multiplicative specification is preferred to an additive specification. The introduction of motivating conditions in model 4 leads to an improvement in the model fit beyond the multiplicative specification. The fit statistic also improves in the fifth model, where the attribute matrix is introduced. The attribute matrix relates brand preferences to attribute preferences, and the coefficient matrix $\Gamma$ associates these preferences with the motivational covariates. The unconstrained matrix of coefficients $\Lambda$ in Equation (12) is much larger (594 elements) than the constrained matrix of $\Gamma$ (342 elements). Despite the large reduction in the number of parameters, we find statistical support for the constrained models. The results provide support for our model of brand preference (Figure 1), in which motivating conditions specify the kinds of attribute respondents are ready to use resources for the right to own and use. The results also indicate that the specification of attribute matrix $A$ is of good quality in capturing the characteristic structure of brands.

**Coefficient Estimates**

Table 8 reports the posterior mean and standard deviation of estimates for elements of matrix $\Gamma$, where $\Gamma$ measures the association between the motivational variables and attribute preferences. Since this is a proprietary study, we disguise the information in Table 8 by masking the attribute labels. Elements with posterior mean larger than two times the posterior standard deviation are displayed in bold. In our analysis, the motivational variables were mean centered. Therefore, the first row of $\Gamma$ indicates the average attribute preference when motivational differences are ignored.

About half of the coefficient estimates in Table 7 are more than two standard deviations from zero. We find that the 342 coefficients in $\Gamma$, plus the 465 unique elements of the random-effects covariance matrix ($\Sigma$) are estimated with a reasonable level of precision, with posterior standard deviations of about 0.25. Estimates of the covariance matrix are available from the authors. These 807 model parameters are estimated with data from 842 respondents, each providing a partial ordering of all 33 brands plus six different complete rankings of five brand-price profiles. The rankings provide very accurate information on five of the brands under study. Preferences for the other 28 brands were inferred from the partial ranking information and the random-effects distribution. In addition, we found the use of the attribute matrix $A$ to be especially helpful in improving the accuracy of the coefficients relative to a model that directly estimates the effect of motivation on brand preference ($\Lambda$) in Equation (12).

To assess the effect size of the motivating conditions, we compute the predicted market shares for each brand when motivations are at the population average versus when they are two units (on the five-point scale) above the population average. Draws from the distribution of brand preferences were generated using estimates from model 5:

$$\beta_{re} = A\hat{\Gamma}z_m + \nu_{re}, \qquad \nu_{re} \sim \text{Normal}(0, \hat{\Sigma}), \quad (15)$$

and averaging the resulting estimates of brand choice probability:

$$\Pr(\text{brand}_i) = \frac{\exp(\beta_i + \beta_p \ln p_i)}{\sum_j \exp(\beta_j + \beta_p \ln p_j)}. \qquad (16)$$

The share estimates at the mean value of the concerns and interests $\bar{z}_m$, closely match the actual market shares of the brands. Furthermore, the changes in market share for a two-unit change in the motives has an interquartile range of 0.02 which was assessed to be reasonable.

## 6. Discussion

Prior research on heterogeneity in brand preference (cf. Allenby and Rossi 1999) has documented the importance of capturing personal descriptors but has tended not to acknowledge the importance of the objective environment and motivation. This is largely due to limitations in the use of revealed market data such as scanner panel data that do not provide information about the origins of demand nor the consumption context. An extended model of choice would begin with demand-creating conditions (i.e., motivations), and include constructs such as desired attributes, brand beliefs, consideration sets, and cost worthiness prior to arriving at the concept of brand preference. While models of extended choice have been proposed in the literature (e.g., Ben-Akiva et al. 1999, McFadden 1986), they have not examined the specific roles of objective environment and motivation on brand preference. This paper should therefore be considered as an initial investigation into the source of brand preference as found in the conditions of the prospect's life outside the marketplace.

Motivating conditions are not uniquely associated with respondents or objective environments. As shown in Table 5, there exists large interrespondent variation in the stated applicability of the motivations within each environmental condition. This aspect of the data, combined with the improvement in model fit due to the motivational variables, suggests that the motivational variables provide a more fine-grained explanation of the origin of brand preference than the respondent and environmental effects. At a strategic

**Table 8 Γ Coefficient Estimates (Posterior Mean and Standard Deviation)**

| | A1 | A2 | A3 | A4 | A5 | A6 | A7 | A8 | A9 | A10 | A11 | A12 | A13 | A14 | A15 | A16 | A17 | A18 | Price |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Constant | **4.34** | **12.42** | **14.18** | **3.87** | **4.25** | **−0.74** | **1.22** | **4.30** | **−1.34** | **7.29** | −0.06 | **−12.02** | **0.20** | **0.53** | **0.84** | **−0.36** | **0.27** | **−0.14** | **−6.87** |
| | **0.26** | **0.32** | **0.40** | **0.19** | **0.26** | **0.28** | **0.44** | **0.31** | **0.21** | **0.19** | 0.18 | **0.19** | **0.02** | **0.04** | **0.07** | **0.03** | **0.03** | **0.01** | **0.13** |
| m1 | **0.78** | **−0.64** | **1.31** | **0.40** | **1.14** | **1.48** | **0.62** | **0.56** | **−0.50** | −0.04 | **0.94** | **1.35** | **−0.05** | **0.20** | **0.30** | **−0.12** | **0.05** | **0.01** | −0.09 |
| | **0.22** | **0.32** | **0.33** | **0.18** | **0.28** | **0.31** | **0.20** | **0.24** | **0.22** | 0.14 | **0.14** | **0.17** | **0.01** | **0.03** | **0.06** | **0.02** | **0.02** | **0.00** | 0.11 |
| m2 | **−0.49** | 0.12 | **−1.42** | **−0.51** | **−0.56** | **−0.44** | **−0.99** | **−0.67** | **1.29** | **−0.51** | −0.19 | **−0.37** | 0.01 | **−0.18** | **−0.30** | **0.08** | 0.02 | **−0.01** | **0.31** |
| | **0.23** | 0.27 | **0.31** | **0.16** | **0.26** | **0.21** | **0.17** | **0.23** | **0.18** | **0.13** | 0.12 | **0.16** | 0.01 | **0.03** | **0.05** | **0.02** | 0.02 | **0.00** | **0.10** |
| m3 | 0.03 | **0.99** | 0.60 | **0.49** | **0.71** | **−0.06** | **1.04** | 0.13 | 0.20 | −0.15 | −0.16 | **−0.46** | **0.06** | **−0.16** | **−0.27** | **0.10** | **0.09** | **−0.02** | −0.27 |
| | 0.32 | **0.27** | 0.37 | **0.20** | **0.31** | **0.29** | **0.20** | 0.33 | 0.21 | 0.24 | 0.15 | **0.18** | **0.02** | **0.04** | **0.09** | **0.02** | **0.02** | **0.00** | 0.16 |
| m4 | **0.57** | −0.15 | **0.91** | **0.52** | **1.16** | **0.81** | **0.93** | **1.04** | −0.03 | 0.44 | **0.54** | 0.07 | **0.10** | **0.08** | 0.13 | **−0.09** | 0.03 | **−0.03** | **−0.10** |
| | **0.31** | 0.27 | **0.38** | **0.19** | **0.27** | **0.33** | **0.22** | **0.37** | 0.21 | 0.23 | **0.21** | 0.18 | **0.02** | **0.04** | 0.08 | **0.02** | 0.02 | **0.00** | **0.12** |
| m5 | 0.44 | **−0.80** | −0.27 | −0.16 | −0.56 | −0.35 | **−0.56** | −0.29 | −0.04 | 0.01 | 0.14 | **0.41** | −0.03 | 0.01 | −0.02 | **0.05** | **−0.09** | **0.02** | **0.35** |
| | 0.23 | **0.28** | 0.37 | 0.17 | 0.30 | 0.23 | **0.25** | 0.28 | 0.22 | 0.14 | 0.13 | **0.18** | 0.02 | 0.04 | 0.06 | **0.02** | **0.02** | **0.00** | **0.13** |
| m6 | −0.25 | −0.01 | −0.57 | −0.13 | **−0.68** | −0.08 | −0.37 | −0.41 | −0.14 | −0.03 | **−0.42** | **−0.55** | **−0.06** | 0.00 | 0.00 | 0.01 | −0.03 | **0.02** | −0.16 |
| | 0.23 | 0.25 | 0.33 | 0.19 | **0.27** | 0.23 | 0.20 | 0.26 | 0.18 | 0.15 | **0.13** | **0.15** | **0.02** | 0.03 | 0.05 | 0.02 | 0.02 | **0.00** | 0.10 |
| m7 | −0.32 | 0.28 | 0.27 | **0.49** | −0.09 | −0.46 | −0.10 | 0.10 | **−0.48** | −0.15 | **0.30** | **−0.36** | −0.01 | **−0.10** | **−0.17** | **0.10** | −0.03 | **0.00** | **−0.34** |
| | 0.24 | 0.30 | 0.31 | **0.16** | 0.33 | 0.26 | 0.20 | 0.25 | **0.18** | 0.18 | **0.14** | **0.15** | 0.02 | **0.03** | **0.05** | **0.02** | 0.02 | **0.00** | **0.12** |
| m8 | **−0.60** | **−0.64** | **−1.72** | **−0.80** | **−1.01** | 0.00 | 1.03 | **−1.05** | **0.49** | **−0.44** | −0.08 | −0.26 | −0.03 | **−0.06** | 0.00 | 0.01 | **−0.04** | **0.02** | **0.20** |
| | **0.19** | **0.25** | **0.27** | **0.15** | **0.25** | 0.21 | 0.19 | **0.24** | **0.19** | **0.14** | 0.12 | 0.14 | 0.01 | **0.03** | 0.05 | 0.02 | **0.02** | **0.00** | **0.10** |
| m9 | **0.70** | **1.15** | **0.96** | **−0.42** | 0.65 | **0.74** | −0.17 | **0.78** | 0.35 | **0.47** | −0.11 | **0.48** | 0.01 | **0.17** | **0.29** | **−0.12** | **0.06** | −0.01 | 0.18 |
| | **0.35** | **0.31** | **0.48** | **0.17** | 0.36 | **0.29** | 0.21 | **0.38** | 0.20 | **0.22** | 0.20 | **0.24** | 0.02 | **0.05** | **0.09** | **0.02** | **0.02** | 0.00 | 0.12 |
| m10 | −0.35 | −0.15 | 0.29 | **−0.42** | 0.25 | 0.15 | 0.07 | 0.13 | −0.40 | −0.08 | 0.13 | **0.56** | **−0.06** | **0.13** | **0.18** | **−0.07** | 0.02 | 0.00 | 0.13 |
| | 0.23 | 0.32 | 0.41 | **0.19** | 0.30 | 0.32 | 0.20 | 0.30 | 0.23 | 0.20 | 0.16 | **0.16** | **0.02** | **0.04** | **0.07** | **0.02** | 0.02 | 0.00 | 0.14 |
| m11 | **0.43** | 0.24 | **−1.31** | −0.12 | **−1.51** | **−1.04** | **−0.70** | **−1.32** | 0.21 | **−0.45** | −0.18 | **−0.51** | **−0.07** | **−0.22** | **−0.32** | **0.16** | **−0.09** | **0.01** | 0.01 |
| | **0.20** | 0.25 | **0.28** | 0.15 | **0.24** | **0.24** | **0.21** | **0.23** | 0.21 | **0.15** | 0.13 | **0.14** | **0.01** | **0.03** | **0.05** | **0.02** | **0.02** | **0.00** | 0.11 |
| m12 | 0.24 | 0.39 | −0.4 | −0.17 | −0.46 | −0.44 | **−0.59** | −0.32 | 0.18 | −0.11 | **−0.25** | −0.10 | **0.03** | 0.03 | 0.07 | 0.02 | **−0.03** | 0.00 | **−0.36** |
| | 0.21 | 0.34 | 0.29 | 0.17 | 0.24 | 0.28 | **0.19** | 0.25 | 0.19 | 0.13 | **0.10** | 0.17 | **0.01** | 0.04 | 0.07 | 0.02 | **0.02** | 0.00 | **0.11** |
| m13 | **1.10** | 0.40 | **0.98** | −0.12 | 0.49 | 0.38 | 0.37 | **0.72** | −0.02 | **0.51** | 0.22 | **0.64** | 0.03 | **0.10** | **0.13** | 0.01 | **−0.04** | 0.00 | 0.20 |
| | **0.22** | 0.32 | **0.29** | 0.18 | 0.25 | 0.26 | 0.22 | **0.25** | 0.19 | **0.16** | 0.13 | **0.20** | 0.02 | **0.03** | **0.06** | 0.02 | **0.02** | 0.00 | 0.16 |
| m14 | **−1.10** | −0.49 | **−1.29** | **0.37** | **−1.20** | **−0.63** | **−1.10** | −0.17 | **0.62** | **−0.37** | **−0.42** | **−0.98** | **0.05** | **−0.29** | **−0.42** | **0.14** | −0.04 | **−0.01** | **−0.37** |
| | **0.26** | 0.35 | **0.43** | **0.19** | **0.36** | **0.32** | **0.26** | 0.35 | **0.23** | **0.20** | **0.16** | **0.20** | **0.02** | **0.06** | **0.10** | **0.03** | 0.02 | **0.00** | **0.15** |
| m15 | 0.38 | −0.37 | **1.16** | −0.05 | **1.10** | 0.45 | **0.68** | **0.78** | −0.10 | 0.12 | **−0.34** | **0.70** | **0.07** | **0.11** | **0.19** | −0.04 | **0.05** | −0.01 | **0.39** |
| | 0.24 | 0.35 | **0.36** | 0.20 | **0.28** | 0.28 | **0.23** | **0.26** | 0.22 | 0.16 | **0.15** | **0.17** | **0.02** | **0.04** | **0.06** | 0.02 | **0.02** | 0.00 | **0.11** |
| m16 | 0.13 | **−0.77** | 0.14 | 0.21 | −0.31 | 0.55 | 0.27 | 0.52 | **−0.49** | 0.03 | 0.13 | −0.25 | **0.04** | 0.09 | 0.14 | **−0.05** | **−0.04** | 0.01 | 0.17 |
| | 0.27 | **0.34** | 0.44 | 0.20 | 0.33 | 0.30 | 0.26 | 0.34 | **0.25** | 0.22 | 0.14 | 0.20 | **0.02** | 0.05 | 0.08 | **0.02** | **0.02** | 0.00 | 0.17 |
| m17 | **−1.11** | −0.61 | **−1.80** | **−0.62** | **−1.26** | −0.54 | −0.37 | **−1.36** | 0.03 | −0.29 | **−0.34** | **−0.66** | **−0.07** | **−0.11** | **−0.12** | **0.10** | **−0.06** | **0.02** | −0.08 |
| | **0.26** | 0.36 | **0.38** | **0.18** | **0.38** | 0.30 | 0.23 | **0.29** | 0.21 | 0.20 | **0.17** | **0.17** | **0.02** | **0.04** | **0.06** | **0.02** | **0.02** | **0.00** | 0.14 |

level, our results imply that firms do not have to formulate their brand to be congruent with a particular kind of respondent or environment. Want-responsive strategies would reflect a subset of the diverse conditions that motivate an individual to use the product category. Our model provides a means of estimating the influence of motivating conditions on attribute and brand preference.

**Attribute-Level Analysis**

Consider, for example, the coefficients reported in Table 8. Demand for attribute A1 increases when respondents are thirsty, enjoy being part of the crowd, want a popular beer, and are thinking about self, past, and future relative to the average motivations in the population. It is less preferred when respondents report that they want to reduce stress, learn about beer, not get too full on the beer, and have fun. This suggests that the attribute is more strongly associated with socially oriented motivations than nonsocial ones. Similarly, attribute A6 has a positive coefficient for motivating condition 4 (enjoy being part of the crowd) and condition 9 (like drinking a popular beer) and a negative coefficient for condition 2 (show refined tastes). This indicates that this attribute tends to be associated with a desire to blend in rather than to stand out in a crowd.

Motivation-specific profiling is also possible with the coefficients in Table 8. For example, under condition 15 (I was bored), attributes A5, A7, A8, A12–A15, and A17 become more important, while attribute A11 becomes relatively less important. Under condition 17 (I was enjoying the way the beer went with food or snacks), many attributes become less important, such as A1, A2–A4, A8, A11–A15, A17, and some become more important such as A16 and A18. The large number of significant coefficients in Table 8 indicates that preference for brands as well as attributes are related to motivating conditions.

**Brand-Level Analysis**

The influence of motivating conditions on the competitive structure of the 33 brands can be assessed by simulating choice shares using Equations (16) and (17) and examining the change in the shares for changes in each of the conditions. Table 9 reports the variation in brand choice share ranks associated with variation in respondent motivation. The base condition reported at the left of Table 9 is the brand rank for our universe of respondents/environments when motivations are at the sample mean of the data. The remaining ranks in the table are obtained by increasing the value of $z_m$ in Equation (14) by two units for each of the 17 motivations. We divide the ranks into four tiers, with brands ranked from 1st to 8th in tier 1, from 9th to 16th in tier 2, from 17th to 24th in tier 3, and from 25th to 33rd in tier 4. For illustration, we compare the brand composition and rankings in each tier under motivating condition 1 (quenching thirst) and condition 17 (enjoying the way the beer goes with food/snacks). As seen from columns m1 and m17 in the table, brands 3 and 18 have the highest ranks when either motivating condition is present. Brands 6, 9, and 19 are in tier 1 when condition 1 is present, but in tier 2 when condition 17 is present. Brands 32 and 33 are ranked in the first tier under condition 17, but the second tier under condition 1. The variation in brand ranks reported in Table 9 illustrates that variation in motivating conditions are associated with large variation in brand preference.

Figure 2 displays the gain or loss in predicted market shares across all the brands for two of the motivating conditions: showing refined tastes, and enjoying the way the beer goes with food/snacks. When the condition ''showing refined tastes'' is found to be more descriptive of the respondent, brands 19, 3, 9, and 14 gain in share while brands 23, 6, and 5 lose. Shares change even more dramatically when the condition is ''enjoying the way the beer goes with food/snacks.'' As shown in Figure 2, a different set of brands now constitutes the gain, neutral, and loss positions. For example, brand 32 enjoys a more than 2% share increase when the motivation is enjoying beer going with food but suffers almost 1% share decrease when the motivation is to show refined tastes. Brand 3 now falls into the loss category while sharing a stronger market position when the previous motivation is present.

Finally, Figure 3 provides a summary of gains and losses across motivational conditions for two popular domestic beers. Brand 2 is more popular when indi-

**Table 9 Brand Rank Under Different Motivating Conditions**

| Legend | Rank | Base | m1 | m2 | m3 | m4 | m5 | m6 | m7 | m8 | m9 | m10 | m11 | m12 | m13 | m14 | m15 | m16 | m17 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 Brand 1 | 1 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| 2 Brand 2 | 2 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 20 | 20 | 18 | 18 | 18 | 18 | 18 | 18 | 18 |
| 3 Brand 3 | 3 | 20 | 20 | 20 | 20 | 2 | 19 | 2 | 20 | 20 | 18 | 18 | 20 | 20 | 19 | 2 | 20 | 2 | 32 |
| 4 Brand 4 | 4 | 2 | 2 | 2 | 19 | 19 | 8 | 20 | 8 | 2 | 2 | 8 | 19 | 2 | 20 | 10 | 10 | 10 | 20 |
| 5 Brand 5 | 5 | 8 | 8 | 8 | 8 | 8 | 20 | 8 | 19 | 4 | 19 | 2 | 2 | 19 | 2 | 4 | 2 | 8 | 8 |
| 6 Brand 6 | 6 | 19 | 6 | 19 | 2 | 20 | 4 | 32 | 2 | 8 | 10 | 33 | 4 | 4 | 4 | 20 | 9 | 20 | 2 |
| 7 Brand 7 | 7 | 10 | 19 | 4 | 9 | 6 | 2 | 19 | 10 | 6 | 8 | 10 | 8 | 32 | 8 | 8 | 19 | 19 | 4 |
| 8 Brand 8 | 8 | 4 | 9 | 6 | 10 | 10 | 32 | 10 | 33 | 23 | 9 | 19 | 32 | 33 | 10 | 6 | 4 | 32 | 33 |
| 9 Brand 9 | 9 | 32 | 10 | 9 | 33 | 9 | 10 | 6 | 32 | 32 | 6 | 9 | 33 | 10 | 32 | 32 | 6 | 6 | 9 |
| 10 Brand 10 | 10 | 6 | 4 | 10 | 4 | 33 | 23 | 33 | 6 | 9 | 23 | 6 | 6 | 8 | 9 | 19 | 32 | 4 | 6 |
| 11 Brand 11 | 11 | 9 | 23 | 23 | 32 | 4 | 9 | 4 | 9 | 19 | 4 | 23 | 10 | 23 | 6 | 33 | 8 | 33 | 10 |
| 12 Brand 12 | 12 | 33 | 27 | 33 | 6 | 32 | 33 | 9 | 4 | 10 | 32 | 32 | 23 | 6 | 33 | 23 | 33 | 9 | 19 |
| 13 Brand 13 | 13 | 23 | 16 | 32 | 16 | 16 | 6 | 23 | 23 | 33 | 33 | 4 | 9 | 9 | 23 | 9 | 23 | 23 | 23 |
| 14 Brand 14 | 14 | 16 | 33 | 16 | 23 | 23 | 16 | 16 | 16 | 16 | 27 | 27 | 16 | 27 | 16 | 1 | 27 | 16 | 16 |
| 15 Brand 15 | 15 | 27 | 32 | 1 | 14 | 27 | 27 | 27 | 30 | 27 | 16 | 16 | 27 | 16 | 27 | 30 | 16 | 27 | 27 |
| 16 Brand 16 | 16 | 14 | 13 | 27 | 30 | 14 | 1 | 1 | 27 | 30 | 1 | 30 | 30 | 30 | 14 | 16 | 14 | 30 | 14 |
| 17 Brand 17 | 17 | 30 | 14 | 30 | 27 | 30 | 30 | 30 | 14 | 13 | 5 | 1 | 14 | 1 | 29 | 27 | 30 | 14 | 1 |
| 18 Brand 18 | 18 | 1 | 30 | 14 | 15 | 13 | 26 | 14 | 1 | 14 | 30 | 14 | 1 | 14 | 30 | 14 | 29 | 13 | 30 |
| 19 Brand 19 | 19 | 13 | 29 | 5 | 1 | 15 | 14 | 26 | 29 | 1 | 29 | 13 | 26 | 26 | 1 | 12 | 1 | 1 | 26 |
| 20 Brand 20 | 20 | 29 | 11 | 15 | 28 | 5 | 29 | 29 | 13 | 5 | 14 | 26 | 29 | 29 | 26 | 29 | 5 | 29 | 13 |
| 21 Brand 21 | 21 | 5 | 26 | 12 | 12 | 11 | 13 | 13 | 12 | 26 | 22 | 29 | 5 | 5 | 5 | 5 | 22 | 15 | 15 |
| 22 Brand 22 | 22 | 26 | 1 | 22 | 5 | 1 | 11 | 5 | 26 | 29 | 13 | 11 | 12 | 13 | 22 | 22 | 15 | 26 | 29 |
| 23 Brand 23 | 23 | 15 | 15 | 28 | 29 | 29 | 5 | 11 | 15 | 12 | 11 | 5 | 13 | 11 | 17 | 15 | 13 | 11 | 12 |
| 24 Brand 24 | 24 | 11 | 5 | 13 | 22 | 22 | 15 | 15 | 11 | 15 | 26 | 15 | 11 | 15 | 13 | 13 | 17 | 12 | 5 |
| 25 Brand 25 | 25 | 12 | 22 | 29 | 17 | 17 | 22 | 22 | 28 | 11 | 15 | 22 | 15 | 22 | 11 | 17 | 26 | 5 | 11 |
| 26 Brand 26 | 26 | 22 | 24 | 11 | 13 | 7 | 17 | 12 | 17 | 22 | 7 | 7 | 22 | 12 | 15 | 11 | 11 | 22 | 22 |
| 27 Brand 27 | 27 | 7 | 7 | 26 | 11 | 28 | 12 | 7 | 5 | 7 | 25 | 17 | 17 | 17 | 12 | 26 | 7 | 17 | 7 |
| 28 Brand 28 | 28 | 28 | 17 | 21 | 26 | 12 | 25 | 28 | 22 | 28 | 12 | 24 | 28 | 28 | 28 | 28 | 28 | 7 | 28 |
| 29 Brand 29 | 29 | 17 | 28 | 25 | 7 | 26 | 7 | 17 | 7 | 21 | 28 | 25 | 21 | 7 | 7 | 21 | 12 | 28 | 25 |
| 30 Brand 30 | 30 | 25 | 12 | 24 | 31 | 21 | 28 | 25 | 25 | 17 | 17 | 12 | 7 | 24 | 24 | 7 | 31 | 25 | 21 |
| 31 Brand 31 | 31 | 21 | 25 | 7 | 21 | 25 | 21 | 21 | 21 | 25 | 24 | 28 | 25 | 21 | 25 | 25 | 25 | 21 | 17 |
| 32 Brand 32 | 32 | 24 | 21 | 17 | 25 | 31 | 24 | 24 | 24 | 24 | 31 | 21 | 24 | 25 | 21 | 24 | 24 | 31 | 24 |
| 33 Brand 33 | 33 | 31 | 31 | 31 | 24 | 24 | 31 | 31 | 31 | 31 | 21 | 31 | 31 | 31 | 31 | 31 | 21 | 24 | 31 |

**Figure 2 Gain and Loss in Market Share Across Brands for Two Motivations**

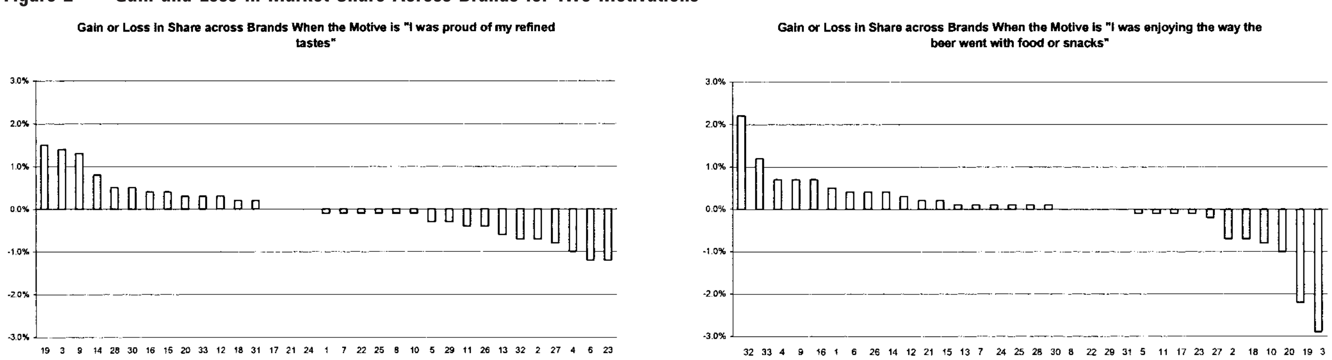
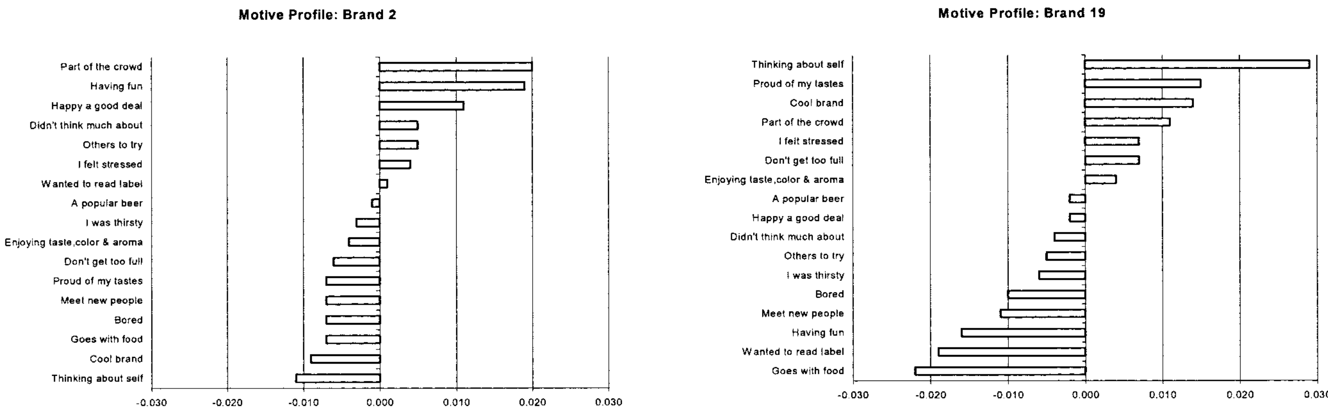


**Figure 3 Motivation Profiles**




viduals want to be part of the crowd, have fun, get a good deal, be indifferent, want others to try their beer, reduce stress, and enjoy reading the label on the bottle. In contrast, brand 19 gains in its market position when the individuals want to think about self, show refined tastes, drink a cool brand of beer, be part of the crowd, reduce stress, not get too full, and enjoy the taste, color, and aroma of beer.

## 7. Concluding Remarks

The source of brand preference is the usefulness of the brand in helping individuals effect an impact on their environment. It is therefore in management's interest that its brand responds to conditions that allocate people's resources. Portraying such conditions is management's means of engaging the attention of its targets in the audiences of media vehicles. Promising and delivering an outcome that is responsive to motivating conditions for which the brand is positioned is a source of value for the user and of return on investment for the producer.

Our analysis documents the existence of large effect sizes for respondent, objective environment and motivating conditions, and the usefulness of using motivating conditions to understand variation in brand preference. Motivating conditions are a promising field for further research and development. When studied, as here, in the form of concerns/interests that prompt individuals to pursue the underlying consumer activity (e.g., consuming beer), they point to the kind of brand attributes that people value.

This study is a first step toward including independent variables that reflect personal and environmental conditions present in the context for the tasks and interests of everyday life, for which goods/services are created and used (Fennell 1978). Features of an expanded model views brand preference as arising from a process that includes motivations, desired attributes, perceptions, and consideration sets that may vary at both at an inter- and intraindividual level. Moreover, such a model would view the intersecting personal and environmental systems as selecting a universe enumerated in person-activity occasions (Fennell 1982, 1997) rather than in persons, households, or groups. Such an expanded model could be applied to any domain of activity and corresponding product use. Accordingly, future research on an extended model of choice that integrates these various components in a common analytic specification will benefit from being conducted in diverse domains.

People engage repeatedly in many of the behaviors studied in marketing. In the case of such behaviors, surveys conducted at a moment in time may require respondents to summarize across occasions, as they enter their answers to specific questions. When the universe is enumerated in person-activity occasions rather than in respondents, researchers are reminded to consider whether or not provision should be made to allow qualitative changes in personal and environmental conditions over occasions of the activity to reflect intraindividual variation, if present. Where the effect of changing objective environment is under study, it is clearly appropriate for the design to permit intraindividual variation to manifest itself.

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## Appendix

The Markov chain Monte Carlo recursions for estimating models 5 and 2 are provided below. The other models are special cases of these models. Model 5 has a standard random-effects specification except for the projection matrix, $A$. Model 2 adds an additional complexity in that a single realization from the random-effect distribution is assumed to be associated with two brand preference vectors that differ because of an additive environmental effect, $\nu_e$. We first specify the Markov chain for model 5, and then provide the changes needed to estimate model 2.

### Model 5

1. Generate $\{[\beta_{re}, e = 1, \ldots, E], r = 1, \ldots, R\}$. The likelihood function is

$$l(\beta_{re}) = \left(\prod_n p_{ren}\right) g_{re}$$

where $n$ indicates the $n$th conjoint choice profile, $p_{ren}$ indicates the probability of the complete choice rankings in conjoint exercises for respondent $r$ in environment $e$, and for the $n$th profile (Equations (6), (7)), and $g_{re}$ indicates the probability of the partial orderings (Equation (2)). The posterior becomes

$$f(\beta_{re} \mid x_{re}, \Sigma) \propto |\Sigma|^{-1/2} \exp[-1/2(\beta_{re} - A\Gamma z_{re})'\Sigma^{-1}(\beta_{re} - A\Gamma z_{re})] \times \left(\prod_n p_{ren}\right) g_{re}.$$

We use the Metropolis-Hastings algorithm with a random walk chain to generate draws of $\beta_{re}$ (see Chib and Greenberg 1995, p. 330, method 1). Let $\beta_{re}^{(p)}$ denote the previous draw, and then the next draw $\beta_{re}^{(n)}$ is given by:

$$\beta_{re}^{(n)} = \beta_{re}^{(p)} + \Delta$$

with the accepting probability $\alpha$ given by:

$$\min\left[\frac{\exp[-1/2(\beta_{re}^{(n)} - A\Gamma z_{re})'\Sigma^{-1}(\beta_{re}^{(n)} - A\Gamma z_{re})]\left(\prod_n p_{ren}(\beta_{re}^{(n)})\right) g_{re}(\beta_{re}^{(n)})}{\exp[-1/2(\beta_{re}^{(p)} - A\Gamma z_{re})'\Sigma^{-1}(\beta_{re}^{(p)} - A\Gamma z_{re})]\left(\prod_n p_{ren}(\beta_{re}^{(p)})\right) g_{re}(\beta_{re}^{(p)})}, 1\right].$$

$\Delta$ is a draw from the density Normal(0, 0.005$I$). The choice for parameters of this density ensures an acceptance rate of over 50%.

2. Generate $\Sigma$. The posterior distribution of $\Sigma$ is inverted Wishart

$$f(\Sigma \mid \beta_{re}, \Gamma) \propto \text{Inverted Wishart} \left[\sum_{e=1}^{E} \sum_{r=1}^{R} (\beta_{re} - A\Gamma z_{re})'(\beta_{re} - A\Gamma z_{re}) + Q_0, RE + q_0\right].$$

$E = 2$, $R = 842$, $Q_0 = 40I$, and $q_0 = 40$ are priors' parameter values where $I$ is the identity matrix.

3. Generate $\Gamma$ (a $p \times m$ matrix, where $p$ is the column dimension of $A$ and $m$ is the row dimension of $z$).

$$\beta_{re} = A\Gamma z_{re} + \nu_{re}, \qquad (A'A)^{-1}A'\beta_{re} = \Gamma z_{re} + (A'A)^{-1}A'\nu_{re}.$$

Let $\delta_{re} = (A'A)^{-1}A'\beta_{re}$ and $u_{re} = (A'A)^{-1}A'\nu_{re}$, and the above equation becomes:

$$\delta_{re} = \Gamma z_{re} + u_{re},$$

where

$$u_{re} \sim MVN(0, \Sigma_*), \qquad \Sigma_* = (A'A)^{-1}A'\Sigma A(A'A)^{-1}.$$

Then stack the data in the following way. That is:

$$\delta = Z\gamma + u$$

where

$$\delta = (\delta_{11}', \ldots, \delta_{1E}', \ldots, \delta_{R1}, \ldots, \delta_{RE}')',$$

$$Z = (I_p \otimes z_{11}', \ldots, I_p \otimes z_{1E}', \ldots, I_p \otimes z_{R1}', \ldots, I_p \otimes z_{RE}')',$$

$$\gamma = \mathrm{vec}(\Gamma') = (\gamma_{11}, \ldots, \gamma_{1m}, \ldots, \gamma_{p1}, \ldots, \gamma_{pm})' \sim MVN(0, 100I),$$

$$u = (u_{11}', \ldots, u_{1E}', \ldots, u_{R1}', \ldots, u_{RE}')'.$$

The posterior distribution of $\gamma$ is:

$$f(\gamma \mid \delta, Z, \Sigma_*^{-1}) \propto MVN(\gamma^*, \Omega^*),$$

where

$$\gamma^* = (Z'(I_{RE} \otimes \Sigma_*^{-1})Z)\Omega^*(Z'(I_{RE} \otimes \Sigma_*^{-1})Z)^{-1}Z'(I_{RE} \otimes \Sigma_*^{-1})\delta,$$

$$\Omega^* = [(Z'(I_{RE} \otimes \Sigma_*^{-1})Z) + 0.01I]^{-1}.$$

### Model 2

Model 2 assumes that the unobserved heterogeneity ($\nu$) is the same for respondent $r$ across environments.

1. Generate $\{[\nu_r, r = 1, \ldots, R\}$. First draw $\nu_r^n$ from its prior distribution: a normal distribution with mean 0 and covariance $\Sigma$. Then form $\beta_{re}^{(n)} = \Gamma z_{re} + \nu_r^{(n)}$. The probability of accepting the new draw is given by (see Chib and Greenberg 1995, p. 330, method 3):

$$\Pr(\text{accepting}) = \min\left[\frac{\prod_e \left(\left(\prod_n p_{ren}(\beta_{re}^{(n)})\right) g_{re}(\beta_{re}^{(n)})\right)}{\prod_e \left(\left(\prod_n p_{ren}(\beta_{re}^{(p)})\right) g_{re}(\beta_{re}^{(p)})\right)}, 1\right].$$

This is different from the random walk chain Metropolis Hasting algorithm which is often used. Since the prior is used to generate draws, it is not used to calculate the probability of move.

2. Generate $\Sigma$. The posterior distribution of $\Sigma$, given $\nu_r$ is inverted Wishart

$$f(\Sigma \mid \nu_r) \propto \text{Inverted Wishart}\left(\sum_{r=1}^{R} \nu_r' \nu_r + Q_0, R + q_0\right).$$

$Q_0 = 40I$ and $q_0 = 40$ are priors where $I$ is the identity matrix.

3. Generate $\Lambda$ (a $q \times m$ matrix, where $q$ is the row dimension of $\beta$ and $m$ is the column dimension of $z$).

$$\beta_{re} = \Lambda z_{re} + \nu_r, \qquad \nu_r \sim MVN(0, \Sigma).$$

Let $\delta_r = \Sigma_e\, \beta_{re}/E$ and $z_r = \Sigma_e\, z_{re}/E$. We then lay out the data in the following way:

$$\delta = Z\gamma + \nu,$$

where

$$\delta = (\delta_1', \ldots, \delta_R')',$$

$$Z = (I_p \otimes z_1', \ldots, I_p \otimes z_R')',$$

$$\gamma = \text{vec}(\Lambda') = \gamma_{11}, \ldots, \gamma_{1m}, \ldots, \gamma_{q1}, \ldots, \gamma_{qm})' \sim MVN(0, 100I),$$

$$\nu = (\nu_1', \nu_2', \ldots, \nu_R')'.$$

The posterior distribution of $\gamma$ is:

$$f(\gamma \mid \delta, Z, \Sigma^{-1}) \propto MVN(\gamma^*, \Omega^*),$$

where

$$\gamma^* = (Z'(I_R \otimes \Sigma^{-1})Z)\Omega^*(Z'(I_R \otimes \Sigma^{-1})Z)^{-1}Z'(I_R \otimes \Sigma^{-1})\delta,$$

$$\Omega^* = [(Z'(I_R \otimes \Sigma^{-1})Z) + 0.01I]^{-1}.$$

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