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# An Integrated Model for Discontinuous Preference Change and Satiation

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# An Integrated Model for Discontinuous Preference Change and Satiation

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**Abstract**

We develop a structural model of horizontal and temporal variety seeking using a dynamic factor model that relates attribute satiation to brand preferences. The factor model employs a threshold specification that triggers preference changes when customer satiation exceeds an admissible level but does not change otherwise. The factor model is developed for high dimensional switching data encountered when multiple brands are purchased across multiple time periods. The model is applied to two scanner-panel datasets where we find distinct shifts in consumer preferences over time where consumers are found to value variety much more than indicated by traditional models. Insights into brand preference are provided by a dynamic joint space map that displays brand positions and temporal changes in consumer preferences over time.

*Keywords:* Dynamic Factor Model, Horizontal Variety, Product Attributes, Threshold Switching Structure

# 1 Introduction

Consumers purchase a variety of goods in every product category, and invariably switch brands at some point in time because of deals or because they get tired of consuming the same things. Temporary changes in preference have been the subject of a long literature on variety seeking in marketing, with reasons ranging from the presence of multiple needs, persons and contexts, to changes in tastes, constraints and available offerings (see McAlister & Pessemier, 1982). This paper investigates the relationship between satiation and preference as an explanation for why people seek variety. We find that consumer satiation affects preferences in a predictable way up to a point, after which consumer preferences abruptly change and consumers switch to varieties that are distinctly different from those consumed in the past. Our findings have implications for the breadth of products carried by retailers.

Existing models of variety seeking assume that changes in the demand for varieties can be explained by a continuous model structure with predictable changes in preference. Models of horizontal variety seeking (Kim et al., 2002; Bhat, 2005), for example, assume that diminishing marginal returns (i.e., satiation) explain why people purchase multiple varieties at one time, where marginal utility is a function of quantity purchased. In these models people are assumed to have stable preferences that diminish in intensity as consumption quantities increase, leading them to tire of consuming large quantities.

Temporal variety seeking behavior is modeled by including lagged purchase variables in models of discrete choice (Dubé et al., 2010; Chintagunta, 1998). A positive coefficient value for lagged purchase leads to higher repurchase probabilities for the consumed product while leaving the preference ordering for the remaining varieties unaffected. Models of temporal variety seeking make relatively minor changes to the preference ordering unless multiple lagged variables are included in the model specification.

A problem common to the study of temporal and horizontal variation of brand purchases is with the dimensionality of switching behavior. The study of $m$ brands is associated with $m^2$ different possible "switches" for two time periods if only one brand is purchased. The dimensionality increases when considering the temporal variation of horizontal variety, where multiple goods are purchased in both time periods. Models of switching behavior are challenged by the large number of possible purchase outcomes, even when the number of brands under study is relatively small.

In this paper we propose a model of preference change that distinguishes multiple forms of variety seeking and examines the temporal relationship between product satiation and brand preference. We find that preference changes are initiated from a latent satiation variable that varies over time, where consumer preferences are stable for a period of time and then abruptly change when the latent satiation variable exceeds a threshold value. This behavior is consistent with consumers becoming tired of consuming the same set of products and then moving on to a new set. We address the issue of dimensionality by employing a dynamic factor model that relates preference and satiation. We find that the best fitting model has the preference factors changing only when the dynamic satiation factor exceeds a threshold. We find that our threshold model has larger estimates of compensating value for varieties in the product line, and has implications for the breadth of offerings carried by retailers.

The organization of the paper is as follows. Section 2 provides a discussion of related literature. In Section 3 we introduce our integrated model and contrast it to existing models of horizontal and temporal variety seeking. We include a discussion of alternative models examined in our empirical analysis that relax some of the assumptions of our proposed model. Section 4 presents empirical results using scanner panel data from two product categories: carbonated beverage and yogurt. In both cases we find significant improvement in model fit over existing models. Section 5 contains a discussion of the results from both data sets to illustrate the insights provided by our approach. Concluding remarks are offered in Section 6.

## 2 Related Literature

Models of discrete behavioral changes, characterized by thresholds and switching regimes, have been found to provide an accurate description of many aspects of consumer behavior. Behavioral decision theory (Einhorn & Hogarth, 1981), for example, describes the effects of framing on consumer decision processes that reflect discrete differences in how consumers view consumption opportunities. The most widely known example of this is how consumers react to gains and losses (Thaler, 1985). More broadly, the similarity, attraction, and compromise effects regularly documented in models of choice (Roe et al., 2001) point to discrete and discontinuous effects in the decision process. The behavioral decision theory literature (e.g., Kahneman & Tversky, 1979) indicates that human behavior reflects discrete, not continuous changes as choice alternatives are described, framed and presented to consumers.

The modeling literature in marketing has also found that models with discrete thresholds provide a good description of marketplace behavior. Switching regression models (Terui & Dahana, 2006), models of structural heterogeneity (Kamakura et al., 1996), and Markov switching models (Frühwirth-Schnatter, 2006) all describe different response processes among and within respondents. Fong and DeSarbo (1981) propose a model of choice in which consumers can enter a passive state of response once they become fatigued. Gilbride and Allenby (2004) propose a choice model with a screening component that sets the choice probability to zero if a brand does not enter a person's consideration set. Terui et al. (2011) find that media advertising for mature products affects brand consideration and choice as long an advertising stock variable is above a threshold variable. We contribute to this literature by showing how these discrete thresholds can be incorporated into the class of direct utility models. In addition, we introduce discrete thresholds in the context of dynamic factor models that allow us to identify the source of abrupt changes in preferences.

Recently, Hasegawa et al. (2012) employ a dynamic factor model on the satiation parameters of a direct utility model to describe changes in preferences over time. Their specification of factor dynamics roughly approximates a smooth time transition function and thus only allows for smooth preference changes. In contrast, our goal is to model discrete shifts in preferences. We do this by integrating the dynamic satiation model of Hasegawa et al. (2012) with a second factor model on baseline preference parameters that contains a discrete switching structure.

Our formulation is consistent with existing models in the marketing and psychology literature. The dynamic attribute satiation (DAS) model of McAlister (1982) and McAlister and Pessemier (1982) predicts that variety seeking occurs as a respondent's consumption history evolves. Sarigollu and Schmittlein (1998) extends the DAS model to include a discrete choice model where preferences are related to an inventory of past attribute accumulation. Our formulation includes the discrete choice model as a special case, and incorporates threshold effects leading to discrete changes in preference. In contrast to Fader and Hardie (1996), we employ a dynamic factor model instead of observed product attributes to deal with high dimensionality of the choices and to allow for temporal variation in demand. One possible motivation for our model is the single peak model by Coombs and Avrunin (1977) in which consumers reach an optimal level of an attribute and then, because of their satiation, decide to consume a different attribute on the next purchase occasion. We investigate changing preferences for brands through a dynamic factor model that, as we see below, helps visualize spatial patterns of competition.

# 3 Model Development

We develop our model within the framework of direct utility maximization (Kim et al., 2002; Bhat, 2005; Hasegawa et al., 2012). Consumer $h$'s utility over $j = 1, \ldots, m$ varieties at time $t$ is defined as:

$$U(\boldsymbol{x}_{ht}) = \sum_{j=1}^{m} \frac{\psi_{jht}}{\gamma_{jht}} \ln(\gamma_{jht} x_{jht} + 1) \tag{1}$$

where $\boldsymbol{x}_{ht} = (x_{1ht}, \ldots, x_{mht})'$ is the vector of quantity demanded by consumer $h$ at time $t$, $\psi_{jht}$ is the baseline value of marginal utility when $x_{jht} = 0$, and $\gamma_{jht}$ is a satiation parameter that affects the rate at which marginal utility diminishes. Both $\psi_{jht}$ and $\gamma_{jht}$ are restricted to be positive.

A stochastic model is obtained by assuming that the baseline utility parameter has an error term. To ensure strictly positive marginal utility, we let $\psi_{jht} = \exp(\psi^*_{jht} + \varepsilon_{jht})$ where $\psi^*_{jht}$ is unrestricted and $\varepsilon_{jht}$ follows an EV(0,1) distribution, as in Bhat (2005). Then the likelihood function is obtained by maximizing (1) subject to the budget constraint $\boldsymbol{p}'_{ht}\boldsymbol{x}_{ht} \leq E_{ht}$ where $\boldsymbol{p}_{ht}$ is the price vector and $E_{ht}$ is total expenditure. This is accomplished by creating the following auxiliary equation.

$$Q = U(\boldsymbol{x}_{ht}) - \lambda(\boldsymbol{p}'_{ht}\boldsymbol{x}_{ht} - E_{ht}). \tag{2}$$

By employing the Kuhn-Tucker conditions of constrained utility maximization, we obtain an expression that relates the observed demand to the error terms as follows:

$$\varepsilon_{jht} = \psi^*_{jht} - \ln(\gamma_{jht} x_{jht} + 1) - \ln p_{jht} \quad \text{if } x_{jht} > 0 \tag{3}$$

$$\varepsilon_{jht} < \psi^*_{jht} - \ln(\gamma_{jht} x_{jht} + 1) - \ln p_{jht} \quad \text{if } x_{jht} = 0 \tag{4}$$

The likelihood function is then composed of a combination of density and probability mass, arising from the interior and corner solutions, respectively.

## 3.1 Satiation Dynamics

We begin our model specification by allowing for satiation dynamics as in Hasegawa et al. (2012). In particular, we let $\boldsymbol{\gamma}^*_{ht} = \log(\boldsymbol{\gamma}_{ht})$ follow a dynamic factor model with a time-invariant factor loading matrix $\boldsymbol{a}$ and a one-dimensional factor $f_{ht}$.

$$\boldsymbol{\gamma}^*_{ht} = \boldsymbol{a} f_{ht} + \varepsilon_{ht},\ \boldsymbol{\varepsilon}_{ht} \sim N(0, \Sigma = \text{diag}\{\sigma_1, \ldots, \sigma_p\}) \quad (5)$$

$$f_{ht} = f_{ht-1} + \nu_{ht},\ \nu_{ht} \sim N(0, 1) \quad (6)$$

The satiation factor score $f_{ht}$ is specified a priori in (6) as a random walk, which imposes a smoothness prior on changes in the factor over time. The random walk specification also allows for the accumulating effects of past purchases, where parameter values of high likelihood rationalize the observed choices. Equation (6) defines a non-parametric model for temporal dynamics, and it accommodates a trend component *locally linear over time* in the non-stationary part worth and satiation parameters. This specification has been successfully used in state space modeling (e.g., Harvey, 1989; Kitagawa & Gersh, 1984; West & Harrison, 1996; Terui et al., 2010; Terui & Ban, 2014).

The factor score moves rather smoothly when the variance of factor score is smaller than the part worth's variance, as is employed and discussed in Hasegawa et al. (2012). When multiplied by the factor loading matrix $\boldsymbol{a}$, the result is a vector of attribute satiation coefficients that evolve through time with expected value $\boldsymbol{a} f_{ht}$. Thus, the factor loading matrix $\boldsymbol{a}$ can indicate for which of the product alternatives consumers experience temporal variation in satiation.

## 3.2 Baseline Preference Dynamics with a Switching Structure

In order to relate satiation dynamics to preference, we specify a second factor model to baseline preference parameters. That is, we assume that the baseline parameters are also well projected into a lower-dimensional space, as is done in a choice map when conducting a market structure analysis (Hauser & Shugan, 2008; Elrod, 1988; Chintagunta, 1994;

Wedel & DeSarbo, 1996).

$$\boldsymbol{\psi}^*_{ht} = \boldsymbol{b}\boldsymbol{g}_{ht} + \boldsymbol{\delta}_{ht},\ \boldsymbol{\delta}_{ht} \sim N(0, V = \text{diag}\{v_1, \ldots, v_m\}) \tag{7}$$

Each row vector of factor loadings matrix $\boldsymbol{b}$ defines the coordinate of brand position and corresponding factor score vector $\boldsymbol{g}_{ht}$, indicating consumer $h$'s preference direction at time $t$. We will refer to $\boldsymbol{g}_{ht}$ as the preference direction vector. We assume that the preference direction will change when consumer satiation level exceeds the admissible level $r_h$, but does not change otherwise. Factor dynamics can then be described as

$$\boldsymbol{g}_{ht} = \begin{cases} \boldsymbol{\beta}_{h1} f^*_{ht-1} + \boldsymbol{\omega}_{ht},\ \boldsymbol{\omega}_{ht} \sim N(0, I) & \text{if } f^*_{ht-1} \geq r_h \\ \boldsymbol{g}_{ht-1} & \text{otherwise} \end{cases} \tag{8}$$

where $\boldsymbol{\beta}_{h1} = (\beta_{h11}, \beta_{h12})'$. We set $r_h = 0$ for identification in the empirical application.

Our model of dynamic preference change integrates two factor analytic models – one for the satiation parameters $\boldsymbol{\gamma}^*_{ht}$ in equation (5) and one for baseline preference parameters $\boldsymbol{\psi}^*_{ht}$ in (7). These parameters are related to each other by (8) where dynamics are explained in terms of the respective factor scores. In our proposed model, the scores for the satiation parameters induce abrupt changes to baseline utility through a threshold model. The dimensionality of the factor models is set to two for the baseline preference parameters for ease of interpretation, and one for the satiation parameters to extract a scalar satiation score. Below we examine alternative specifications for these model components, including the model by Hasegawa et al. (2012) who consider a factor model for the baseline utility preference parameters only.

## 3.3 Alternative Models

We consider six alternative models in addition to our proposed model. All models differ on the basis of dynamics, switching behavior, and flexibility. The first alternative model employs a static preference direction using an ordinary factor model, and is denoted as (Static).

$$\boldsymbol{\psi}_{ht}^{*} = \boldsymbol{b}\boldsymbol{g}_{h} + \boldsymbol{\delta}_{ht},\ \boldsymbol{\delta}_{ht} \sim N(0, V = \mathrm{diag}\{v_1, \ldots, v_m\}) \tag{9}$$

Here preferences are assumed to have constant expected value $\boldsymbol{b}\boldsymbol{g}_{h}$ that is unrelated to satiation effects.

The second alternative is a dynamic model that assumes the preference direction vector $\boldsymbol{g}_{ht}$ follows a random walk:

$$\boldsymbol{g}_{ht} = \boldsymbol{g}_{ht-1} + \boldsymbol{\omega}_{ht},\ \boldsymbol{\omega}_{ht} \sim N(0, I) \tag{10}$$

This specification is identical to a non-parametric model of a stochastic trend in time series $\{\boldsymbol{g}_{ht}\}$. Equation (10) has no causal variables or structural parameters, and we refer to this model as a non-parametric dynamic factor model (NDF). This specification was successfully employed in Hasegawa et al. (2012) to capture the locally linear stochastic trend for a non-stationary series.

The third model specifies the preference direction vector $\boldsymbol{g}_{ht}$ as being related to satiation in the previous period:

$$\boldsymbol{g}_{ht} = \boldsymbol{\beta}_{h1} f_{ht-1}^{*} + \boldsymbol{\omega}_{ht},\ \boldsymbol{\omega}_{ht} \sim N(0, I) \tag{11}$$

We call the model represented by (12) as the structured dynamic factor model (SDF). Both the NDF and SDF have a common property that preference changes whenever a consumer purchases a product.

The next set of models include a switching mechanism regarding the timing of preference change. We assume that satiation drives the change when its level exceeds a threshold value, and does not drive the change otherwise. These models have various forms, or types. The first is an SDF model with threshold switching, called a switching non-parametric dynamic factor model (SNDF):

$$\boldsymbol{g}_{ht} = \begin{cases} \boldsymbol{g}_{ht-1} + \boldsymbol{\omega}_{ht},\ \boldsymbol{\omega}_{ht} \sim N(0, I) & \text{if } f^*_{ht-1} \geq r_h \\ \boldsymbol{g}_{ht-1} & \text{otherwise} \end{cases} \tag{12}$$

The second model is our proposed switching structured dynamic factor model (SSDF1) shown in (8). The third model is composed of the two previous models, called a hybrid dynamic factor model (SSDF2):

$$\boldsymbol{g}_{ht} = \begin{cases} \boldsymbol{\beta}_{h1} f^*_{ht-1} + \boldsymbol{g}_{ht-1} + \boldsymbol{\omega}_{ht},\ \boldsymbol{\omega}_{ht} \sim N(0, I) & \text{if } f^*_{ht-1} \geq r_h \\ \boldsymbol{g}_{ht-1} & \text{otherwise} \end{cases} \tag{13}$$

This model provides a flexible specification of the preference vector updating equation, allowing the current preference vector to be influenced by both the satiation variable and the past preference vector. It allows the expected preference vector to the informed by the satiation variable but not entirely dependent on it.

The fourth model includes an autoregressive term $\boldsymbol{\beta}_{h2}$ in the model to allow for greater flexibility relative to equation (14). This model is referred to as SSDF3:

$$\boldsymbol{g}_{ht} = \begin{cases} \boldsymbol{\beta}_{h1} f^*_{ht-1} + \boldsymbol{\beta}_{h2} \boldsymbol{g}^*_{ht-1} + \boldsymbol{\omega}_{ht},\ \boldsymbol{\omega}_{ht} \sim N(0, I) & \text{if } f^*_{ht-1} \geq r_h \\ \boldsymbol{g}_{ht-1} & \text{otherwise} \end{cases} \tag{14}$$

These models provide a comprehensive set for assessing the benefit of the proposed dynamic model for describing preference change. Table 1 provides a summary of all models that are fit to the data.

Table 1: Summary of Models

| Model | Dynamic | Switching | Equation | Specification | |
|---|---|---|---|---|---|
| Static | No | No | (9) | $\boldsymbol{g}_{ht} = \boldsymbol{g}_h$ | |
| NDF | Yes | No | (10) | $\boldsymbol{g}_{ht} = \boldsymbol{g}_{ht-1} + \boldsymbol{\omega}_{ht}$ | |
| SDF | Yes | No | (11) | $\boldsymbol{g}_{ht} = \boldsymbol{\beta}_{h1} f^*_{ht-1} + \boldsymbol{\omega}_{ht}$ | |
| SNDF | Yes | Yes | (12) | $\boldsymbol{g}_{ht} = \boldsymbol{g}_{ht-1} + \boldsymbol{\omega}_{ht}$ | if $f^*_{ht-1} \geq r_h$ |
| SSDF1 | Yes | Yes | (8) | $\boldsymbol{g}_{ht} = \boldsymbol{\beta}_{h1} f^*_{ht-1} + \boldsymbol{\omega}_{ht}$ | if $f^*_{ht-1} \geq r_h$ |
| SSDF2 | Yes | Yes | (13) | $\boldsymbol{g}_{ht} = \boldsymbol{\beta}_{h1} f^*_{ht-1} + \boldsymbol{g}_{ht-1} + \boldsymbol{\omega}_{ht}$ | if $f^*_{ht-1} \geq r_h$ |
| SSDF3 | Yes | Yes | (14) | $\boldsymbol{g}_{ht} = \boldsymbol{\beta}_{h1} f^*_{ht-1} + \boldsymbol{\beta}_{h2} f^*_{ht-1} + \boldsymbol{\omega}_{ht}$ | if $f^*_{ht-1} \geq r_h$ |

# 4 Empirical Applications

## 4.1 Data Description

We apply the model to the carbonated beverage and yogurt categories in the IRI household panel data set (see Bronnenberg et al., 2008 for a detailed description). The product categories are chosen because of their wide assortments and high frequency of purchase among households. We use data over a two-year period from one store in Pittsfield, Massachusetts.

In the carbonated beverage category, we restrict our analysis to 12-packs of cans (the most common form) and select the top 30 varieties based on total volume. The resulting product set consists of nine national brands (7Up, A&W, Barqs, Coke, Mountain Dew, Mug, Pepsi, Schweppes, Sprite) and one private label brand. A complete description of the product set is provided in Table A.1. A total of 607 households are included in our data set after removing those with less than five purchases over the sample period. Moreover, 56% of purchase occasions correspond to interior solutions in which more than one variety is chosen.

In the yogurt category, we select six national brands (Colombo, Dannon Fruit on the Bottom, Dannon Light and Fit, Stonyfield Farm, Yoplait, and Yoplait Light) and one private label brand. We then choose the top five varieties within each brand based on market share. A complete description of the resulting 35 products is provided in Table A.2.

This data set contains 387 households and 80% interior solutions. The overwhelming majority of interior solutions in both data sets points to the need of a demand model that can accommodate this multiple discreteness.

We also observe characteristics in the data which point to the need to accommodate temporal variety seeking. For example, in the two-year sample period, 92.1% and 83.9% of households have purchased more than one brand in the carbonated beverage and yogurt categories, respectively. Further evidence is shown in Figure 1, which plots the purchases for a single household (ID#50) in the yogurt category. We find concentration among Private Label varieties for the first 10 trips, and then a shift to Dannon and Yoplait varieties during the last 10 trips. This type of demand pattern is consistent with abrupt shifts in preferences over time.

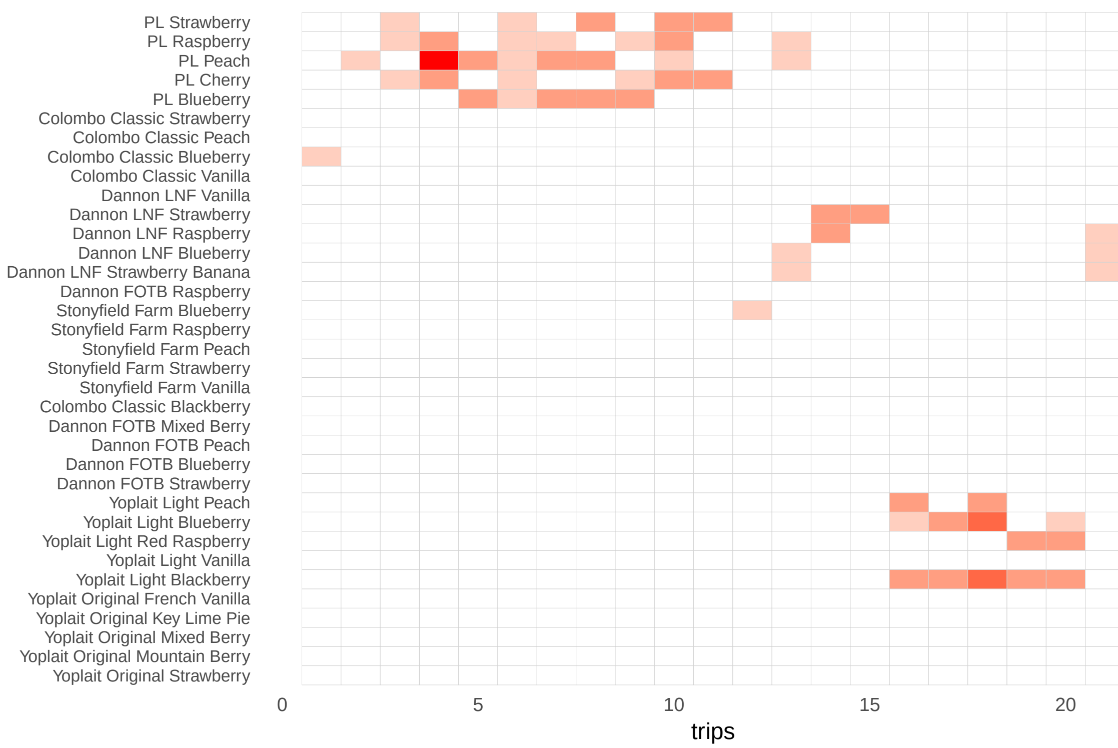



Figure 1: An example of temporal changes in household purchases (ID#50) in the yogurt category.

## 4.2 Identification Conditions and Prior Specification

We fit seven models to the data as described in Section 3.3. All models are specified as Bayesian models and Markov chain Monte Carlo methods are used to sample from each posterior distribution. Descriptions of the algorithms used are provided in Appendix B. For the two-factor model applied to baseline parameters, we restrict the loadings to achieve statistical identification.

$$\boldsymbol{b} = \begin{pmatrix} 1 & 0 \\ b_{21} & 1 \\ b_{31} & b_{32} \\ \vdots & \vdots \\ b_{p1} & b_{p2} \end{pmatrix} \tag{15}$$

This restriction due to the factor model being applied to parameters of a latent utility is stronger than Geweke and Zhou (1996) condition for the conventional factor model. We define the prior distribution on this factor model's parameters as follows:

$$\begin{aligned} v_k^2 &\sim IG(n_{v0}/2, s_{v0}/2) \\ b_{21} &\sim N(b_0, B_0) \\ \boldsymbol{b}_k = (b_{k1}, b_{k2})' &\sim N(\boldsymbol{b}_0, B_0) \quad \text{for } 3 \leq k \leq p \end{aligned} \tag{16}$$

where $n_{v0} = s_{v0} = 2$, $b_0 = 0$, and $B_0 = 100I$. The same type of priors are applied to the one-factor model for satiation dynamics:

$$\begin{aligned} \sigma_k^2 &\sim IG(n_{\sigma 0}/2, s_{0\sigma}/2) \\ a_{k1} &\sim N(a_0, A_0) \quad \text{for } 2 \leq k \leq p \end{aligned} \tag{17}$$

where $n_{\sigma 0} = s_{v\sigma 0} = 2$, $a_0 = 0$, and $A_0 = 100I$. Finally, the hierarchical prior on the switching coefficients is specified as:

$$\begin{aligned} \beta_{h1k} &\sim N(\bar{\beta}_{1k}, 1) \\ \bar{\beta}_{1k} &\sim N(\bar{\beta}_0, \nu_0) \end{aligned} \tag{18}$$

where $\bar{\beta}_0 = 0$ and $\nu_0 = 10$.

## 4.3 Computation

Applying MCMC methods to our high dimensional choice model presents significant computational challenges. MCMC is a time consuming technique and the model scales exponentially in the number of alternatives and households. We overcome these challenges by employing parallel computing, which allocates the sampling procedure for the set of household-level parameters to a set of 144 cores of CPU. The common parameters in the distribution of heterogeneity can be updated in the usual fashion (e.g., Gibbs sampling). This approach drastically reduces computational time from more than several months to only a couple of days.

## 4.4 Estimation Results

Table 2 reports measures of in-sample and predictive model fit. In-sample fit is evaluated using the log marginal density (LMD) and Bayesian deviance information criterion (DIC). The LMD statistic is calculated using the Newton-Raftery algorithm (Newton & Raftery, 1994). The DIC is a statistic used for model comparison that explicitly penalizes model complexity (Spiegelhalter et al., 2002). Predictive fit is evaluated using root-mean-squared-error (RMSE). We use the last observation from each panelist and compute

$$RMSE = \sqrt{\frac{1}{Hm}\sum_{h=1}^{H}\sum_{j=1}^{m}(x_{j,T_h+1} - \hat{x}_{j,T_h+1})^2} \tag{19}$$

where $\hat{x}_{j,T_h+1}$ is the predicted demand for individual $h$ at time $T_h + 1$. Demand forecasts are generated by maximizing the utility function in (1) subject to the budget constraint $\boldsymbol{p}'_{h,T_h+1}\boldsymbol{x}_{h,T_h+1} \leq E_{h,T_h+1}$, where $\boldsymbol{p}_{h,T_h+1}$ and $E_{h,T_h+1}$ are fixed at average price and expenditure levels during the in-sample period.

Table 2: Model Fit

| | Carbonated Beverage | | | Yogurt | | |
|---|---|---|---|---|---|---|
| | in-sample | | out-of-sample | in-sample | | out-of-sample |
| Model | LMD | DIC | RMSE | LMD | DIC | RMSE |
| Static | -1090.049 | 10914.347 | 3.098 | -859.523 | 8210.251 | 6.042 |
| NDF | -850.912 | 10366.264 | 3.155 | -844.130 | 8193.423 | 5.965 |
| SNDF | -876.193 | 9969.135 | 2.593 | -792.194 | 7952.334 | 5.551 |
| SSDF1 | **-809.822** | **8911.165** | 1.980 | **-586.123** | **6851.133** | 3.351 |
| SSDF2 | -1012.713 | 9438.858 | **1.653** | -670.514 | 7124.513 | 3.415 |
| SSDF3 | -866.639 | 9561.690 | 2.135 | -620.107 | 7095.019 | **3.005** |

Across both data sets, we find that allowing for dynamics in baseline preferences provides an improvement in in-sample and predictive fit over the static model of Hasegawa et al. (2012). Our proposed suite of models that add a switching structure based on satiation dynamics further improves model fit. Specifically, the SSDF1 specification provides the best in-sample fit to the data. This suggests that any gains in flexibility offered by relating preference dynamics to both satiation and past preference (models SSDF2 and SSDF3) do not outweigh the costs of estimating more parameters. Moreover, the predictive fit for model SSDF1 is only outperformed by other dynamic switching models. This is evidence in support of accommodating this discrete switching behavior in our data.

Estimates of parameters in model SSDF1 are provided in Appendix C. Specifically, tables C.1 and C.2 provide estimates of baseline preference and satiation parameters for the carbonated beverage data, and tables C.3 and C.4 do the same for the yogurt data. Across both data sets, we find that estimates of baseline preferences are roughly proportional to purchase shares, which helps validate our results. Table 3 reports the estimates of $\bar{\beta}_{11}$ and $\bar{\beta}_{12}$, which represent the effects of previous satiation levels on preference. In particular, these estimates indicate the average effect across households on the direction of change with respect to previous satiation. We find that the preference vector of an average consumer tends to rotate clockwise as previous satiation levels increase for both categories.

Table 3: Switching Equation Estimates

| | Carbonated Beverage | | Yogurt | |
|---|---|---|---|---|
| | Mean | SD | Mean | SD |
| $\bar{\beta}_{11}$ | 0.275 | (1.512) | 0.351 | (0.958) |
| $\bar{\beta}_{12}$ | -0.201 | (1.321) | -0.119 | (0.101) |

Figure 2 illustrates the heterogeneity of preference change across both data sets. We measure preference change for household $h$ by computing the proportion of times the switching equation in (8) is turned on over the course of $R$ iterations and $T_h$ choices.

$$k_h = \frac{1}{R}\frac{1}{T_h}\sum_{r=1}^{R}\sum_{t=2}^{T_h} I(f_{ht-1}^{*(r)} \geq 0). \tag{20}$$

Here we call $k_h \in (0, 1)$ a propensity score for preference change, where large values indicate frequent change and small values indicate stable preferences. We find the distribution of propensity scores to be very different between the two product categories. In the carbonated beverage category, most households either exhibit extremely stable or extremely dynamic preferences. In the yogurt category, the majority of households exhibit changing preferences.

Figure 3 shows histograms of estimated coefficients on the switching equation. The left and right figures plot estimates of the first and second preference directions, respectively. We find the tails of the distribution to be much longer in the yogurt data, with a left-skew in the second preference direction. The patterns of rotation of preference vector are heterogeneous, with some households have different signs implying moves in different directions. There are also a significant number of households who have estimates very close to zero, implying no change on one or both dimensions.

(a) Carbonated Beverage (b) Yogurt

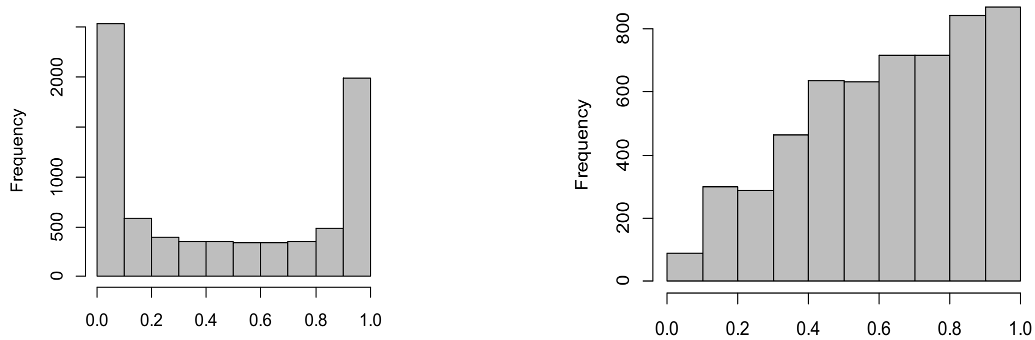
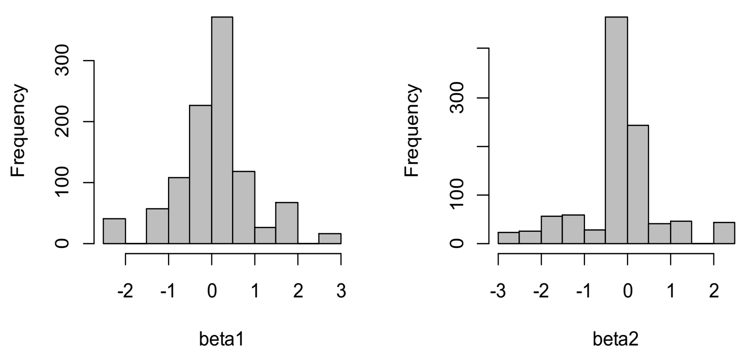



Figure 2: Distributions of heterogeneity for the individual propensity score of preference change.

(a) Carbonated Beverages




(b) Yogurt

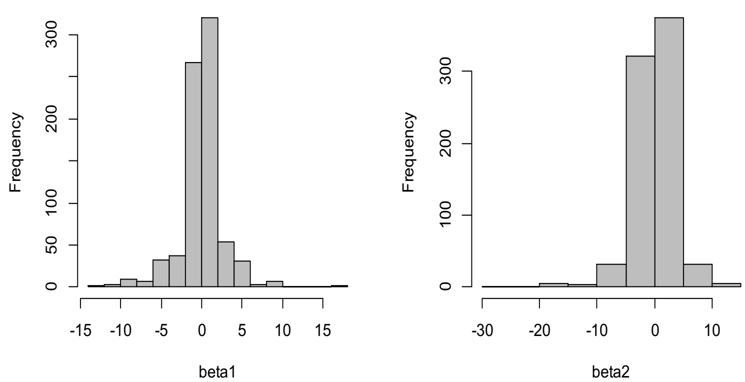



Figure 3: Distributions of heterogeneity for the coefficients of switching equations.

# 5 Implications

In this section, we investigate two possible implications of our model of preference dynamics. First, we discuss the impact of dynamics on the value of product assortments and compare the compensating values implied by the dynamic factor model to those from a traditional static model. The results indicate that varieties are more highly valued with the proposed dynamic model, implying that consumer highly value wide assortments. We also examine the dynamics of preference change by considering three households with different preference patterns that either exhibit frequent changes over time, moderately frequent change, and non-changing preferences. We then consider how estimates for individual consumers are related to observed purchase behavior and switching structures. The dynamic joint space maps are depicted.

## 5.1 Compensating Values

Compensating value ($CV$) is measured by first computing the maximum attainable utility from the observed choices using our utility model.

$$V_{ht}(\boldsymbol{p}_{ht}, E_{ht}|\boldsymbol{\theta}_h) = \max_{\boldsymbol{x}_{ht}} U(\boldsymbol{x}_{ht}|\boldsymbol{\theta}_h) \;\text{ such that }\; \boldsymbol{p}'_{ht}\boldsymbol{x}_{ht} = E_{ht} \tag{21}$$

The posterior mean of parameters $\boldsymbol{\theta}_h = (\boldsymbol{\psi}_h, \boldsymbol{\gamma}_h, \boldsymbol{\beta}_h)$ and the observed values of $\boldsymbol{p}_{ht}$ and $E_{ht}$ are inserted into (21) to obtain $\boldsymbol{x}_{ht}$ and $V_{ht}$ for each household $h$ and choice occasion $t$. We also calculate maximum attainable utility under the case of product $i$ being removed from the choice set.

$$V^{(i)}_{ht}(\boldsymbol{p}_{ht}, E_{ht}|\boldsymbol{\theta}_h) = \max_{\boldsymbol{x}_{ht}} U(\boldsymbol{x}_{ht}|\boldsymbol{\theta}_h) \;\text{ such that }\; \boldsymbol{p}'_{ht}\boldsymbol{x}_{ht} = E_{ht} \text{ and } x_{iht} = 0. \tag{22}$$

We then find the value $CV_{ht}^{(i)}$ such that $V_{ht}$ and $V_{ht}^{(i)}$ are equal.

$$V_{ht}(\boldsymbol{p}_{ht}, E_{ht}) = V_{ht}^{(i)}(\boldsymbol{p}_{ht}, E_{ht} + CV_{ht}^{(i)}) \tag{23}$$

The set of CV estimates are provided in Appendix D. We report the median of the distribution of heterogeneity, as near-zero estimates of the satiation parameter can lead to large compensating values and a right-skewed distribution. We also report estimates of CV as a share of budget, denoted $PCV_h^{(i)} = CV_h^{(i)} / \sum_t E_{ht}$. Table D.1 and Table D.2 compare CV and PCV estimates for the static model and proposed dynamic model. Both tables indicate significantly larger values of CV and PCV for dynamic model. This means that the value of product assortments in the store is underestimated by static model, and the variety of products are supported by dynamism of consumer preference through their experience.

## 5.2 Preference Dynamics

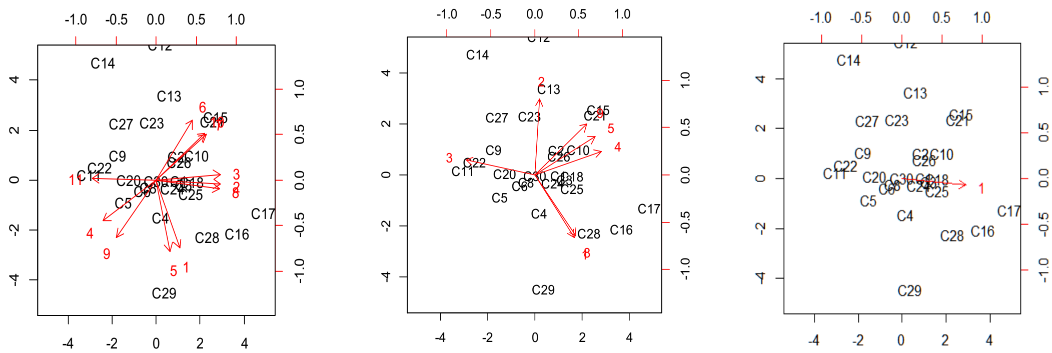
Figure 4 plots preference directions for three households from each data set. The top panel corresponds to the carbonated beverage category and the bottom corresponds to the yogurt category. Below each plot of preference directions, we provide the set of household estimates of the preference switching model parameters. For the sake of brevity, we will limit our discussion to the carbonated beverage data.

Figure 4a shows that the preference direction associated with the purchase occasions of household #314. The associated purchase records indicate positive demand across many varieties, the satiation score ($f_{ht}$) remains at a high level, and the switching mechanism works such that the coordinates in the attributed space move all the time. This consumer can be characterized as a variety seeker. The satiation level affects both coordinates positively, and this impact is much greater for the first dimension.

In contrast, Figure 4c provides the map and parameter estimates for household #66,

## Carbonated Beverage Data

(a) Frequent Change #314 | (b) Occasional Change #122 | (c) Little Change #66



**(a) Frequent Change #314**

| $t$ | $f_{ht}$ | $g_{ht1}$ | $g_{ht2}$ | $k_{ht}$ |
|---|---|---|---|---|
| 1 | -0.637 | 0.480 | -1.222 | 1.000 |
| 2 | 0.551 | 2.563 | -0.144 | 0.808 |
| 3 | -0.002 | 2.752 | 0.227 | 0.756 |
| 4 | 0.389 | -0.470 | -0.319 | 0.798 |
| 5 | 0.718 | 0.118 | -0.534 | 0.870 |
| 6 | 1.095 | 0.811 | 1.169 | 0.988 |
| 7 | 1.337 | 0.325 | 0.260 | 0.894 |
| 8 | 1.878 | 3.154 | -0.388 | 0.733 |
| 9 | 0.960 | -0.395 | -0.503 | 0.835 |
| 10 | 0.568 | 1.895 | 1.619 | 0.999 |
| 11 | 1.203 | -1.641 | 0.043 | 0.989 |
| 12 | 0.734 | 3.002 | -1.292 | 0.788 |

**(b) Occasional Change #122**

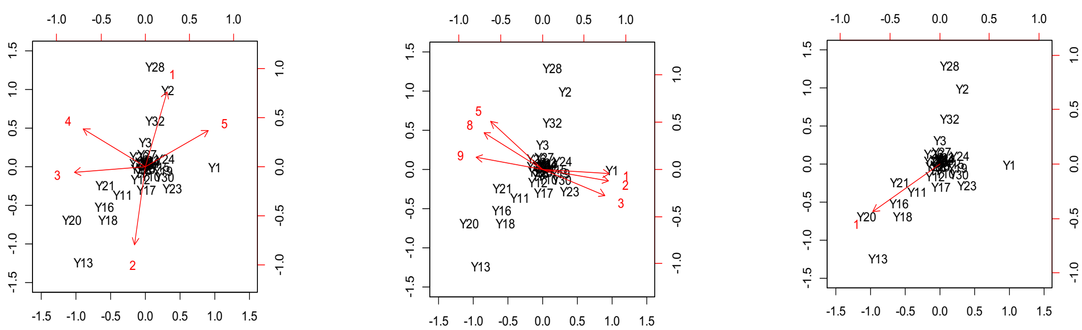
| $t$ | $f_{ht}$ | $g_{ht1}$ | $g_{ht2}$ | $k_{ht}$ |
|---|---|---|---|---|
| 1 | -1.121 | 1.078 | -1.569 | 1.000 |
| 2 | 0.409 | 0.123 | 1.682 | 0.740 |
| 3 | -0.006 | -1.395 | 0.281 | 0.923 |
| 4 | 0.233 | 1.787 | 0.586 | 0.972 |
| 5 | -0.618 | 1.964 | 1.141 | 0.886 |
| 6 | -1.043 | 1.485 | 1.290 | 0.460 |
| 7 | -0.670 | -0.289 | 1.716 | 0.431 |
| 8 | -1.185 | 1.380 | -1.872 | 0.526 |
| 9 | 0.525 | 1.065 | 0.952 | 0.970 |

**(c) Little Change #66**

| $t$ | $f_{ht}$ | $g_{ht1}$ | $g_{ht2}$ | $k_{ht}$ |
|---|---|---|---|---|
| 1 | -2.491 | 2.987 | -0.275 | 1.000 |
| 2 | -3.567 | 2.149 | -1.716 | 0.331 |
| 3 | -4.267 | 0.457 | 0.168 | 0.080 |
| 4 | -5.172 | 0.803 | -2.743 | 0.031 |
| 5 | -5.692 | 0.546 | -0.266 | 0.133 |
| 6 | -4.727 | -1.084 | 0.015 | 0.013 |
| 7 | -5.066 | 0.160 | 2.499 | 0.001 |
| 8 | -4.577 | 1.372 | -0.653 | 0.001 |

## Yogurt Data

(d) Frequent Change #251 | (e) Occasional Change #18 | (f) Little Change #15



**(d) Frequent Change #251**

| $t$ | $f_{ht}$ | $g_{ht1}$ | $g_{ht2}$ | $k_{ht}$ |
|---|---|---|---|---|
| 1 | 1.872 | 0.122 | 0.381 | 1.000 |
| 2 | 2.477 | -0.018 | -0.123 | 0.928 |
| 3 | 2.211 | -0.331 | -0.024 | 0.828 |
| 4 | 2.289 | -0.119 | 0.065 | 0.946 |
| 5 | 2.182 | 0.129 | 0.066 | 0.866 |
| 6 | 2.214 | -0.418 | -0.037 | 0.919 |

**(e) Occasional Change #18**

| $t$ | $f_{ht}$ | $g_{ht1}$ | $g_{ht2}$ | $k_{ht}$ |
|---|---|---|---|---|
| 1 | 0.034 | 0.400 | -0.024 | 1.000 |
| 2 | 0.373 | 0.800 | -0.121 | 0.742 |
| 3 | 0.502 | 0.353 | -0.130 | 0.821 |
| 4 | 1.219 | -0.158 | 0.215 | 0.459 |
| 5 | -0.272 | -0.175 | 0.145 | 0.974 |
| 6 | 0.139 | -0.321 | 0.101 | 0.491 |
| 7 | 0.038 | 0.177 | -0.010 | 0.465 |
| 8 | 0.028 | -0.350 | 0.194 | 0.653 |
| 9 | 0.573 | -0.096 | 0.015 | 0.643 |
| 10 | 0.434 | -0.167 | -0.016 | 0.846 |

**(f) Little Change #15**

| $t$ | $f_{ht}$ | $g_{ht1}$ | $g_{ht2}$ | $k_{ht}$ |
|---|---|---|---|---|
| 1 | -1.729 | -1.997 | -1.292 | 1.000 |
| 2 | -1.284 | -1.663 | -1.485 | 0.041 |
| 3 | -1.711 | -2.226 | -1.205 | 0.263 |
| 4 | -1.073 | -1.814 | -1.373 | 0.123 |
| 5 | -1.721 | -1.712 | -1.527 | 0.180 |
| 6 | -1.502 | -1.658 | -1.321 | 0.169 |

Figure 4: Preference directions for three households are plotted from each data set. The top panel corresponds to carbonated beverage bottom corresponds to yogurt. We also provide the set of household estimates of the preference switching model parameters.

which exhibits no preference changes. For instance, in the data we observe this household to purchase caffeine free Diet Coke or Diet Pepsi in 73% shopping trips. The satiation level negatively and positively affects the first and second coordinates to change, respectively, and it is much greater for the first coordinate. Together, these figures demonstrate the flexibility of the proposed dynamic model for studying preferences.

# 6 Concluding Remarks

In this paper we develop a model of dynamic variety seeking that relates preference changes to brand satiation. Two dynamic factor models are developed for baseline and satiation parameters in a direct utility model of horizontal variety that are integrated so that preference can change abruptly when the satiation factor score exceeds a threshold level. We find strong empirical support for our model in two datasets, and provide evidence that wide product assortments are undervalued when dynamic preference changes are ignored. Our model is motivated by theories of adoption and change similar to McAlister (1982) and McAlister and Pessemier (1982), who proposed a framework for relating satiation to preference. The presence of different operating regimes also has a long history in the marketing and psychology literature (e.g., Coombs & Avrunin, 1977).

We compare our model to six alternative specifications, including a static model implying that preference does not change at all, a dynamic model without a switching structure on preference change, and dynamic models with switching structures. The models in the last category are composed of non-parametric local linear trend, parametric regression, and their hybrid models. When applied to two household panel data sets, both measures of model fit support the model with a switching structure and parametric regression.

The empirical applications demonstrate that abrupt preference changes are common, as the majority of consumers are found to change their preferences over the course of their purchase history. Our results indicate that the standard modeling assumption of static preferences may not always hold, particularly in light of the large increase in model fit for our proposed dynamic models. We find that consumers with wider varieties of purchases tend to change their preferences more often – that is, through periodic shifts in preference as described by the model. This finding is consistent with consumers having well defined tastes that vary through time, as opposed to broad tastes for which many brands will suffice. Our results are consistent with emerging evidence of binge behavior, or "clumpliness" in consumer demand that is not consistent with the notion of stable preferences (Zhang et al., 2015).

Future research is needed to understand the context of purchase and consumption. Our results indicate that the unit of analysis for heterogeneity is not the respondent, but instead the respondent at a specific purchase occasion who is influenced by their past decisions and other factors. Additional work is needed to identify and integrate these factors and past events into models of consumer decision making that allow marketers to anticipate shifts in preference. We believe that the temporal study of satiation, and other triggers of preference change, is a fruitful area for future research.

# A Product Descriptions

Table A.1: Product Descriptions – Carbonated Beverage

| | Variety | Incidence | Quantity | Corner Solutions | | Interior Solutions | |
|---|---|---|---|---|---|---|---|
| C1 | Pepsi | 788 | 1460 | 428 | (0.54) | 360 | (0.46) |
| C2 | Diet Pepsi | 429 | 773 | 221 | (0.52) | 208 | (0.48) |
| C3 | Mountain Dew | 214 | 288 | 63 | (0.29) | 151 | (0.71) |
| C4 | Pepsi CF | 193 | 316 | 96 | (0.50) | 97 | (0.50) |
| C5 | Diet Pepsi CF | 285 | 480 | 148 | (0.52) | 137 | (0.48) |
| C6 | Wild Cherry Pepsi | 126 | 149 | 49 | (0.39) | 77 | (0.61) |
| C7 | Schweppes | 195 | 242 | 87 | (0.45) | 108 | (0.55) |
| C8 | Coke CF | 242 | 407 | 109 | (0.45) | 133 | (0.55) |
| C9 | Sprite | 673 | 860 | 170 | (0.25) | 503 | (0.75) |
| C10 | Diet Coke | 783 | 1391 | 366 | (0.47) | 417 | (0.53) |
| C11 | Diet Sprite | 270 | 411 | 100 | (0.37) | 170 | (0.63) |
| C12 | Diet Coke CF | 536 | 1044 | 289 | (0.54) | 247 | (0.46) |
| C13 | Cherry Coke | 98 | 124 | 17 | (0.17) | 81 | (0.83) |
| C14 | Coke | 1631 | 2950 | 872 | (0.53) | 759 | (0.47) |
| C15 | Barqs | 145 | 163 | 46 | (0.32) | 99 | (0.68) |
| C16 | A&W | 41 | 51 | 37 | (0.90) | 4 | (0.10) |
| C17 | 7Up | 151 | 193 | 64 | (0.42) | 87 | (0.58) |
| C18 | Diet 7Up | 134 | 172 | 71 | (0.53) | 63 | (0.47) |
| C19 | Mug | 172 | 193 | 69 | (0.40) | 103 | (0.60) |
| C20 | PL Cola | 754 | 1050 | 354 | (0.47) | 400 | (0.53) |
| C21 | PL Cream Soda | 379 | 456 | 134 | (0.35) | 245 | (0.65) |
| C22 | PL Cherry | 91 | 100 | 25 | (0.27) | 66 | (0.73) |
| C23 | PL Fruit Punch Soda | 105 | 125 | 20 | (0.19) | 85 | (0.81) |
| C24 | PL Ginger Ale | 483 | 584 | 196 | (0.41) | 287 | (0.59) |
| C25 | PL Grape | 299 | 352 | 81 | (0.27) | 218 | (0.73) |
| C26 | PL Lemon Lime | 261 | 282 | 74 | (0.28) | 187 | (0.72) |
| C27 | PL Orange | 882 | 1130 | 396 | (0.45) | 486 | (0.55) |
| C28 | PL Diet Ginger Ale | 357 | 447 | 223 | (0.62) | 134 | (0.38) |
| C29 | PL Diet Orange | 286 | 405 | 80 | (0.28) | 206 | (0.72) |
| C30 | PL Root Beer | 318 | 480 | 117 | (0.37) | 201 | (0.63) |
| | TOTAL | 11321 | 17078 | 5002 | (0.44) | 6319 | (0.56) |

Notes: CF = Caffeine Free, PL = Private Label

Table A.2: Product Descriptions – Yogurt

| | Variety | Incidence | Quantity | Corner Solutions | | Interior Solutions | |
|---|---|---|---|---|---|---|---|
| Y1 | Yoplait Original Strawberry | 383 | 680 | 90 | (0.23) | 293 | (0.77) |
| Y2 | Yoplait Original Mountain Berry | 392 | 819 | 80 | (0.20) | 312 | (0.80) |
| Y3 | Yoplait Original Mixed Berry | 432 | 886 | 111 | (0.26) | 321 | (0.74) |
| Y4 | Yoplait Original Key Lime Pie | 383 | 824 | 145 | (0.38) | 238 | (0.62) |
| Y5 | Yoplait Original French Vanilla | 330 | 744 | 116 | (0.35) | 214 | (0.65) |
| Y6 | Yoplait Light Blackberry | 327 | 604 | 26 | (0.08) | 301 | (0.92) |
| Y7 | Yoplait Light Vanilla | 260 | 714 | 64 | (0.25) | 196 | (0.75) |
| Y8 | Yoplait Light Red Raspberry | 285 | 491 | 25 | (0.09) | 260 | (0.91) |
| Y9 | Yoplait Light Blueberry | 318 | 656 | 31 | (0.10) | 287 | (0.90) |
| Y10 | Yoplait Light Peach | 269 | 482 | 20 | (0.07) | 249 | (0.93) |
| Y11 | Dannon FOTB Strawberry | 147 | 232 | 12 | (0.08) | 135 | (0.92) |
| Y12 | Dannon FOTB Blueberry | 228 | 457 | 50 | (0.22) | 178 | (0.78) |
| Y13 | Dannon FOTB Peach | 121 | 239 | 26 | (0.21) | 95 | (0.79) |
| Y14 | Dannon FOTB Mixed Berry | 170 | 295 | 29 | (0.17) | 141 | (0.83) |
| Y15 | Colombo Classic Blackberry | 351 | 619 | 76 | (0.22) | 275 | (0.78) |
| Y16 | Stonyfield Farm Vanilla | 122 | 247 | 29 | (0.24) | 93 | (0.76) |
| Y17 | Stonyfield Farm Strawberry | 156 | 218 | 13 | (0.08) | 143 | (0.92) |
| Y18 | Stonyfield Farm Peach | 188 | 302 | 18 | (0.10) | 170 | (0.90) |
| Y19 | Stonyfield Farm Raspberry | 197 | 339 | 21 | (0.11) | 176 | (0.89) |
| Y20 | Stonyfield Farm Blueberry | 201 | 395 | 32 | (0.16) | 169 | (0.84) |
| Y21 | Dannon FOTB Raspberry | 145 | 247 | 21 | (0.14) | 124 | (0.86) |
| Y22 | Dannon LNF Strawberry Banana | 302 | 522 | 46 | (0.15) | 256 | (0.85) |
| Y23 | Dannon LNF Blueberry | 462 | 790 | 102 | (0.22) | 360 | (0.78) |
| Y24 | Dannon LNF Raspberry | 414 | 700 | 81 | (0.20) | 333 | (0.80) |
| Y25 | Dannon LNF Strawberry | 319 | 537 | 59 | (0.18) | 260 | (0.82) |
| Y26 | Dannon LNF Vanilla | 402 | 1014 | 177 | (0.44) | 225 | (0.56) |
| Y27 | Colombo Classic Vanilla | 358 | 974 | 134 | (0.37) | 224 | (0.63) |
| Y28 | Colombo Classic Blueberry | 503 | 1223 | 138 | (0.27) | 365 | (0.73) |
| Y29 | Colombo Classic Peach | 387 | 763 | 64 | (0.17) | 323 | (0.83) |
| Y30 | Colombo Classic Strawberry | 453 | 866 | 77 | (0.17) | 376 | (0.83) |
| Y31 | PL Blueberry | 453 | 975 | 55 | (0.12) | 398 | (0.88) |
| Y32 | PL Cherry | 462 | 982 | 87 | (0.19) | 375 | (0.81) |
| Y33 | PL Peach | 423 | 697 | 41 | (0.10) | 382 | (0.90) |
| Y34 | PL Raspberry | 386 | 674 | 39 | (0.10) | 347 | (0.90) |
| Y35 | PL Strawberry | 484 | 1004 | 60 | (0.12) | 424 | (0.88) |
| | TOTAL | 11213 | 22211 | 2195 | (0.20) | 9018 | (0.80) |

Notes: FOTB = Fruit on the Bottom, LNF = Light & Fit, PL = Private Label

# B MCMC Algorithms

Below we describe our approach from sampling from each parameter's full conditional distribution.

1. $\boldsymbol{\psi}^*_{ht}|\boldsymbol{x}_{ht}, \boldsymbol{\gamma}^*_{ht}, \boldsymbol{b}, \boldsymbol{g}_{ht}, V$

$$p(\boldsymbol{\psi}^*_{ht}|\boldsymbol{x}_{ht}, \boldsymbol{\gamma}^*_{ht}, \boldsymbol{b}, \boldsymbol{g}_{ht}, V) \\ \propto \det|V|^{-1/2} \exp\left\{-\frac{1}{2}(\boldsymbol{\psi}_{ht} - \boldsymbol{b}\boldsymbol{g}_{ht})' V^{-1} (\boldsymbol{\psi}_{ht} - \boldsymbol{b}\boldsymbol{g}_{ht})\right\} \quad \times L_{ht}(\boldsymbol{\psi}_{ht}) \tag{B.1}$$

The term $L_{ht}(\boldsymbol{\psi}_{ht})$ is the likelihood function for consumer $h = 1, \ldots, H$ at purchase time $t = 1, \ldots, T_h$, where the likelihood function is composed of a combination of density and mass, arising from the interior and corner solutions, respectively, and is defined for experimental data as

$$L = \phi(g_1, \ldots, g_{n_1})|J| \times \int_{-\infty}^{g_{n_1+1}} \cdots \int_{-\infty}^{g_m} f(\varepsilon_{g_{n_1}}, \ldots, \varepsilon_m) d\varepsilon_{g_{n_1}} \cdots d\varepsilon_m \tag{B.2}$$

where the probability mass function can be evaluated in closed-form due to EV(0,1) errors. We sample from this posterior using a Metropolis-Hastings algorithm using random-walk proposals of the form

$$\boldsymbol{\psi}^{*(r)}_{ht} = \boldsymbol{\psi}^{*(r-1)}_{ht} + \boldsymbol{\lambda}_\psi, \ \ \boldsymbol{\lambda}_\psi \sim N(0, k \cdot I) \tag{B.3}$$

where $k$ was chosen to be 0.5.

2. $\boldsymbol{\gamma}^*_{ht}|\boldsymbol{x}_{ht}, \boldsymbol{\psi}^*_{ht}, \boldsymbol{a}, f_{ht}, \Sigma$

$$p(\boldsymbol{\gamma}^*_{ht}|\boldsymbol{x}_{ht}, \boldsymbol{\psi}^*_{ht}, \boldsymbol{a}, f_{ht}, \Sigma) \\ \propto \det|\Sigma|^{-1/2} \exp\left\{-\frac{1}{2}(\boldsymbol{\gamma}^*_{ht} - \boldsymbol{a} f_{ht})' V^{-1} (\boldsymbol{\gamma}^*_{ht} - \boldsymbol{a} f g_{ht})\right\} \quad \times L_{ht}(\boldsymbol{\gamma}^*_{ht}) \tag{B.4}$$

We again use a random-walk Metropolis-Hastings algorithm:

$$\boldsymbol{\gamma}_{ht}^{*(r)} = \boldsymbol{\gamma}_{ht}^{*(r-1)} + \boldsymbol{\lambda}_\gamma,\ \boldsymbol{\lambda}_\gamma \sim N(0, k' \cdot I) \tag{B.5}$$

where $k'$ was chosen to be 0.5.

3. $\boldsymbol{a}|\boldsymbol{\gamma}_{ht}^*, f_{ht}, \Sigma$

   Under the assumption of uncorrelated $a_k$'s, we define $\boldsymbol{f}_h = (f_{h1}, \ldots, f_{hT_h})'$ to be a $T_h$-dimensional vector and let $\boldsymbol{f} = (\boldsymbol{f}'_1, \ldots, \boldsymbol{f}'_H)'$ be a $(\sum_h T_h)$-dimensional vector. We define $\boldsymbol{\gamma}_{hk}$ and $\bar{\boldsymbol{\gamma}}_k$ in an analogous fashion. Then, the posterior can be derived from a normal regression equation with coefficient parameter vector $\bar{\boldsymbol{\gamma}}_k$ and explanatory matrix $\boldsymbol{f}$. That is,

$$a_k|\boldsymbol{\gamma}_{ht}^*, f_{ht}, \Sigma \sim N(\hat{a}_k, A_k) \tag{B.6}$$

   where $A_k = (A_0^{-1} + \sigma_k^{-1}\boldsymbol{f}'\boldsymbol{f})^{-1}$ and $\hat{a}_k = A_k(A_0^{-1}a_0 + \sigma_k^{-1}\boldsymbol{f}'\bar{\boldsymbol{\gamma}}_k)$. The identification condition is considered when $k \leq 1$.

4. $\boldsymbol{b}|\boldsymbol{\psi}_{ht}^*, \boldsymbol{g}_{ht}, V$

   As in step (3), we define $\boldsymbol{g}_h = (\boldsymbol{g}_{h1}, \ldots, \boldsymbol{g}_{hT_h})'$ to be a $T_h \times 2$ matrix, $\boldsymbol{g} = (\boldsymbol{g}'_1, \ldots, \boldsymbol{g}'_H)'$ a $(\sum_h T_h) \times 2$ matrix, $\boldsymbol{\psi}_{hj}^* = (\psi_{h1j}^*, \ldots, \psi_{hT_hj})'$ a $T_h$-dimensional vector, and $\bar{\boldsymbol{\psi}}_j^* = (\boldsymbol{\psi}_{1j}^{*'}, \ldots, \boldsymbol{\psi}_{Hj}^{*'})'$ a $(\sum_h T_h)$-dimensional vector. Just as before,

$$\boldsymbol{b}_j|\boldsymbol{\psi}_{ht}^*, \boldsymbol{g}_{ht}, V \sim N(\hat{\boldsymbol{b}}_j, B_j) \tag{B.7}$$

   where $B_j = (B_0^{-1} + v_j^{-1}\boldsymbol{g}'\boldsymbol{g})^{-1}$ and $\hat{\boldsymbol{b}}_j = B_j(B_0^{-1}\boldsymbol{b}_0 + v_j^{-1}\boldsymbol{g}'\bar{\boldsymbol{\psi}}_j)$. The identification condition is considered when $j \leq 2$.

5. $f_{ht}, \boldsymbol{g}_{ht}|\boldsymbol{\gamma}_{ht}^*, \boldsymbol{\psi}_{ht}^*, \Sigma, V$

   We reformulate the measurement equation as

$$\begin{pmatrix} \boldsymbol{\gamma}_{ht}^* \\ \boldsymbol{\psi}_{ht}^* \end{pmatrix} = \begin{pmatrix} \boldsymbol{a} & 0 \\ 0 & \boldsymbol{b} \end{pmatrix} \begin{pmatrix} f_{ht} \\ \boldsymbol{g}_{ht} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\varepsilon}_{ht} \\ \boldsymbol{\delta}_{ht} \end{pmatrix}, \quad \begin{pmatrix} \boldsymbol{\varepsilon}_{ht} \\ \boldsymbol{\delta}_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} \Sigma & 0 \\ 0 & V \end{pmatrix}\right) \tag{B.8}$$

as well as the system equation as

$$\begin{pmatrix} f_{ht} \\ \boldsymbol{g}_{ht} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ -K_{ht}\boldsymbol{\beta}_{h1} & (1-K_{ht})I \end{pmatrix} \begin{pmatrix} f_{ht-1} \\ \boldsymbol{g}_{ht-1} \end{pmatrix} + \begin{pmatrix} \nu_{ht} \\ \boldsymbol{\omega}_{ht} \end{pmatrix}, \quad \begin{pmatrix} \nu_{ht} \\ \boldsymbol{\omega}_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} 1 & 0 \\ 0 & K_{ht} \end{pmatrix}\right) \tag{B.9}$$

where $\boldsymbol{\beta}_{h1} = (\beta_{h11}, \beta_{h12})'$ and $K_{ht} = I(f_{ht-1}^* \geq r_h)$. We use Carter and Kohn (1994) for a time-varying coefficient in the state space model described above.

6. SSDF1: $\boldsymbol{\beta}_1 = (\beta_{11}, \beta_{12})' | f_{ht}, \boldsymbol{g}_{ht}, \bar{\boldsymbol{\beta}}_1$

$$\beta_{h1k} \sim N(\hat{\beta}_{h1k}, (\boldsymbol{f}_h^{*'} \boldsymbol{f}_h + 1)^{-1} \ k = 1, 2 \tag{B.10}$$

where $\hat{\beta}_{h1k} = (\tilde{\boldsymbol{f}}_h^{*'} \tilde{\boldsymbol{f}}_h + 1)^{-1} (\tilde{\boldsymbol{f}}_h^{*'} \tilde{\boldsymbol{g}}_{hk} + \bar{\beta}_{1k})$ and $\tilde{\boldsymbol{f}}_h^* = -\tilde{\boldsymbol{f}}_h$ and $\tilde{\boldsymbol{f}}_h$ and $\tilde{\boldsymbol{g}}_{hk}$ are the data matrix and vector, respectively, collected in the case of $f_{ht-1} \geq r_h$. If $\tilde{\boldsymbol{f}}_h =$ (i.e., $K_{ht} = 0$ for all $t$), the posterior is $\beta_{h1k} \sim N(\bar{\beta}_{1k}, 1)$ by homogeneity.

7. SSDF1: $\bar{\boldsymbol{\beta}}_1 = (\bar{\beta}_{11}, \bar{\beta_{12}})' | \boldsymbol{\beta}_{11}, \ldots, \boldsymbol{\beta}_{H1}, v_{\beta_0}$

$$\bar{\beta}_{1k} \sim N(\hat{\beta}_{1k}, (H + v_{\beta_0})^{-1} \ k = 1, 2 \tag{B.11}$$

where $\hat{\beta}_{h1k} = (H + v_{\beta_0})^{-1} (\sum_h \beta_{hk} + v_{\beta_0}^{-1} \beta_0)$.

8. SSDF3: $\boldsymbol{\beta}_{h1} = (\beta_{h11}, \beta_{h12})', \boldsymbol{\beta}_{h2} = (\beta_{h21}, \beta_{h22})' | f_{ht}, \boldsymbol{g}_{ht}, \bar{\boldsymbol{\beta}}_1, \bar{\boldsymbol{\beta}}_2$

   The parameters $\boldsymbol{\beta}_{h1}$, $\boldsymbol{\beta}_{h2}$, $\bar{\boldsymbol{\beta}}_1$, and $\bar{\boldsymbol{\beta}}_2$ are sampled according to the MCMC procedure of the standard hierarchical Bayesian regression model shown above.

$$\boldsymbol{\beta}_{hk} \sim N(\bar{\boldsymbol{\beta}}_k, I) \tag{B.12}$$

We use the data $\tilde{\boldsymbol{f}}_h$ and $\tilde{\boldsymbol{g}}_{hk}$ when $f_{ht-1} \geq r_h$. If $\tilde{\boldsymbol{f}}_h =$ (i.e., $K_{ht} = 0$ for all $t$), the posterior is $\boldsymbol{\beta}_{hk} \sim N(\bar{\boldsymbol{\beta}}_k, I)$.

# C Estimation Results

Table C.1: Baseline Preference Estimates – Carbonated Beverage

| | $\boldsymbol{\psi}^*$ | | $\boldsymbol{b}$ | | | | $V$ | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | | SD | | Mean | SD |
| Pepsi | 0.365 | (0.091) | 1.000 | - | - | - | 0.391 | (0.259) |
| Diet Pepsi | 0.107 | (0.086) | 0.883 | 1.000 | (0.025) | - | 0.901 | (0.166) |
| Mountain Dew | -0.023 | (0.081) | 1.247 | -0.146 | (0.028) | (0.038) | 0.730 | (0.271) |
| Pepsi CF | -0.360 | (0.102) | 0.173 | -1.459 | (0.031) | (0.032) | 0.550 | (0.231) |
| Diet Pepsi CF | -0.071 | (0.130) | -1.503 | -0.851 | (0.049) | (0.028) | 0.071 | (0.354) |
| Wild Cherry Pepsi | -0.226 | (0.079) | -0.662 | -0.383 | (0.028) | (0.038) | 0.966 | (0.394) |
| Schweppes | -0.012 | (0.099) | 5.996 | -2.523 | (0.027) | (0.029) | 0.715 | (0.298) |
| Coke CF | -0.038 | (0.099) | -0.400 | -0.257 | (0.027) | (0.035) | 0.662 | (0.245) |
| Sprite | 0.388 | (0.099) | -1.768 | 1.021 | (0.032) | (0.027) | 0.848 | (0.333) |
| Diet Coke | 0.683 | (0.091) | 1.832 | 1.015 | (0.028) | (0.028) | 0.446 | (0.162) |
| Diet Sprite | -0.038 | (0.138) | -3.036 | 0.225 | (0.027) | (0.029) | 0.550 | (0.138) |
| Diet Coke CF | 0.089 | (0.156) | 0.184 | 5.463 | (0.022) | (0.032) | 0.542 | (0.228) |
| Cherry Coke | -0.310 | (0.129) | 0.608 | 3.435 | (0.024) | (0.025) | 0.726 | (0.247) |
| Coke | 1.721 | (0.098) | -2.421 | 4.769 | (0.031) | (0.037) | 0.546 | (0.323) |
| Barqs | -0.170 | (0.103) | 2.708 | 2.589 | (0.023) | (0.034) | 0.455 | (0.167) |
| A&W | -0.275 | (0.109) | 3.671 | -2.079 | (0.028) | (0.032) | 0.984 | (0.402) |
| 7Up | -0.027 | (0.101) | 4.876 | -1.272 | (0.025) | (0.032) | 0.177 | (0.366) |
| Diet 7Up | -0.168 | (0.109) | 1.591 | -0.034 | (0.021) | (0.031) | 0.417 | (0.224) |
| Mug | -0.314 | (0.095) | -1.146 | -7.595 | (0.031) | (0.029) | 1.240 | (0.341) |
| PL Cola | 0.279 | (0.113) | -1.256 | 0.071 | (0.025) | (0.035) | 0.430 | (0.250) |
| PL Cream Soda | -0.107 | (0.097) | 2.553 | 2.370 | (0.028) | (0.025) | 1.331 | (0.097) |
| PL Cherry | -0.415 | (0.078) | -2.552 | 0.535 | (0.023) | (0.038) | 0.320 | (0.239) |
| PL Fruit Punch Soda | -0.445 | (0.082) | -0.212 | 2.345 | (0.025) | (0.026) | 0.774 | (0.198) |
| PL Ginger Ale | 0.053 | (0.131) | 0.759 | -0.295 | (0.026) | (0.033) | 0.097 | (0.290) |
| PL Grape | -0.124 | (0.130) | 1.589 | -0.507 | (0.034) | (0.023) | 0.755 | (0.350) |
| PL Lemon Lime | -0.260 | (0.107) | 1.028 | 0.759 | (0.028) | (0.029) | 0.642 | (0.401) |
| PL Orange | 0.460 | (0.120) | -1.584 | 2.307 | (0.031) | (0.035) | 0.374 | (0.368) |
| PL Diet Ginger Ale | -0.259 | (0.101) | 2.307 | -2.258 | (0.029) | (0.032) | 1.070 | (0.440) |
| PL Diet Orange | -0.440 | (0.113) | 0.357 | -4.447 | (0.027) | (0.044) | 0.349 | (0.269) |
| PL Root Beer | - | - | - | - | - | - | - | - |

Notes: CF = Caffeine Free, PL = Private Label

Table C.2: Satiation Estimates – Carbonated Beverage

| | $\gamma^*$ | | $\boldsymbol{a}$ | | $\Sigma$ | |
|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD |
| Pepsi | 0.643 | (0.243) | 1.000 | - | 1.484 | (0.144) |
| Diet Pepsi | 0.747 | (0.477) | 0.605 | (0.033) | 0.934 | (0.103) |
| Mountain Dew | 0.213 | (0.455) | 0.014 | (0.034) | 0.552 | (0.057) |
| Pepsi CF | 0.295 | (0.299) | 0.075 | (0.032) | 0.695 | (0.112) |
| Diet Pepsi CF | 0.003 | (0.297) | 0.390 | (0.021) | 0.493 | (0.134) |
| Wild Cherry Pepsi | -0.444 | (0.351) | -0.203 | (0.031) | 0.661 | (0.043) |
| Schweppes | 0.100 | (0.290) | -0.007 | (0.026) | 0.913 | (0.081) |
| Coke CF | 0.238 | (0.285) | -0.032 | (0.044) | 0.546 | (0.139) |
| Sprite | -0.531 | (0.393) | -0.010 | (0.029) | 0.926 | (0.130) |
| Diet Coke | 0.657 | (0.249) | -0.001 | (0.028) | 0.309 | (0.064) |
| Diet Sprite | 0.504 | (0.491) | -0.054 | (0.031) | 0.957 | (0.154) |
| Diet Coke CF | 0.270 | (0.261) | 0.041 | (0.030) | 0.159 | (0.116) |
| Cherry Coke | 0.188 | (0.244) | -0.106 | (0.033) | 0.646 | (0.091) |
| Coke | -0.543 | (0.215) | -0.147 | (0.023) | 0.626 | (0.074) |
| Barqs | 0.087 | (0.238) | -0.364 | (0.032) | 0.536 | (0.120) |
| A&W | 0.444 | (0.424) | 0.102 | (0.030) | 0.429 | (0.089) |
| 7Up | -0.520 | (0.448) | 0.253 | (0.029) | 0.618 | (0.036) |
| Diet 7Up | -0.168 | (0.412) | -0.101 | (0.035) | 1.235 | (0.053) |
| Mug | 0.676 | (0.249) | 0.336 | (0.028) | 1.000 | (0.257) |
| PL Cola | -0.660 | (0.557) | 0.328 | (0.029) | 0.548 | (0.139) |
| PL Cream Soda | 0.083 | (0.394) | 0.134 | (0.036) | 0.430 | (0.150) |
| PL Cherry | -0.842 | (0.295) | -0.416 | (0.025) | 0.632 | (0.197) |
| PL Fruit Punch Soda | -0.261 | (0.379) | -0.380 | (0.034) | 0.272 | (0.107) |
| PL Ginger Ale | 0.125 | (0.281) | 0.190 | (0.030) | 0.090 | (0.045) |
| PL Grape | -0.241 | (0.424) | -0.106 | (0.025) | 0.704 | (0.159) |
| PL Lemon Lime | 0.249 | (0.302) | 0.180 | (0.023) | 0.953 | (0.083) |
| PL Orange | -0.028 | (0.370) | -0.056 | (0.030) | 0.929 | (0.034) |
| PL Diet Ginger Ale | -0.131 | (0.160) | -0.456 | (0.025) | 0.789 | (0.097) |
| PL Diet Orange | 0.216 | (0.453) | 0.192 | (0.033) | 0.339 | (0.130) |
| PL Root Beer | 0.047 | (0.422) | 0.387 | (0.029) | 0.763 | (0.116) |

Notes: CF = Caffeine Free, PL = Private Label

Table C.3: Baseline Preference Estimates – Yogurt

| | $\boldsymbol{\psi}^*$ | | $\boldsymbol{b}$ | | | | $V$ | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | | SD | | Mean | SD |
| Yoplait Original Strawberry | 0.279 | (0.108) | 1.000 | - | - | - | 0.211 | (0.188) |
| Yoplait Original Mountain Berry | 0.139 | (0.089) | 0.326 | 1.000 | (0.019) | - | 0.300 | (0.360) |
| Yoplait Original Mixed Berry | 0.163 | (0.151) | -0.001 | 0.325 | (0.029) | (0.032) | 0.134 | (0.373) |
| Yoplait Original Key Lime Pie | 0.093 | (0.131) | 0.088 | 0.034 | (0.025) | (0.004) | 0.093 | (0.318) |
| Yoplait Original French Vanilla | 0.071 | (0.032) | 0.039 | 0.043 | (0.017) | (0.018) | 0.338 | (0.226) |
| Yoplait Light Blackberry | 0.031 | (0.181) | 0.037 | 0.074 | (0.032) | (0.046) | 0.255 | (0.286) |
| Yoplait Light Vanilla | -0.109 | (0.071) | -0.056 | -0.070 | (0.032) | (0.023) | 0.471 | (0.364) |
| Yoplait Light Red Raspberry | 0.016 | (0.113) | -0.009 | -0.023 | (0.027) | (0.039) | 0.333 | (0.181) |
| Yoplait Light Blueberry | 0.017 | (0.162) | 0.019 | 0.039 | (0.033) | (0.025) | 0.411 | (0.066) |
| Yoplait Light Peach | -0.158 | (0.018) | 0.071 | -0.111 | (0.007) | (0.031) | 0.528 | (0.317) |
| Dannon FOTB Strawberry | -0.240 | (0.051) | -0.329 | -0.348 | (0.007) | (0.022) | 0.195 | (0.113) |
| Dannon FOTB Blueberry | -0.052 | (0.131) | -0.068 | -0.157 | (0.034) | (0.019) | 0.191 | (0.141) |
| Dannon FOTB Peach | -0.393 | (0.079) | -0.889 | -1.221 | (0.012) | (0.033) | 0.356 | (0.213) |
| Dannon FOTB Mixed Berry | -0.272 | (0.158) | 0.062 | 0.085 | (0.023) | (0.025) | 0.295 | (0.131) |
| Colombo Classic Blackberry | 0.074 | (0.110) | 0.216 | 0.010 | (0.029) | (0.018) | 0.244 | (0.050) |
| Stonyfield Farm Vanilla | -0.390 | (0.112) | -0.591 | -0.509 | (0.026) | (0.027) | 0.169 | (0.118) |
| Stonyfield Farm Strawberry | -0.211 | (0.086) | 0.018 | -0.283 | (0.033) | (0.033) | 0.255 | (0.280) |
| Stonyfield Farm Peach | -0.323 | (0.182) | -0.540 | -0.673 | (0.029) | (0.023) | 0.359 | (0.352) |
| Stonyfield Farm Raspberry | -0.180 | (0.077) | 0.249 | -0.033 | (0.014) | (0.021) | 0.254 | (0.281) |
| Stonyfield Farm Blueberry | -0.301 | (0.166) | -1.057 | -0.676 | (0.036) | (0.016) | 0.397 | (0.209) |
| Dannon FOTB Raspberry | -0.304 | (0.187) | -0.576 | -0.221 | (0.019) | (0.012) | 0.355 | (0.227) |
| Dannon LNF Strawberry Banana | -0.012 | (0.175) | -0.070 | -0.013 | (0.029) | (0.057) | 0.238 | (0.175) |
| Dannon LNF Blueberry | 0.294 | (0.082) | 0.388 | -0.271 | (0.024) | (0.024) | 0.199 | (0.244) |
| Dannon LNF Raspberry | 0.146 | (0.107) | 0.283 | 0.115 | (0.035) | (0.032) | 0.246 | (0.068) |
| Dannon LNF Strawberry | -0.023 | (0.118) | 0.005 | -0.012 | (0.035) | (0.027) | 0.274 | (0.077) |
| Dannon LNF Vanilla | 0.142 | (0.185) | -0.089 | 0.152 | (0.030) | (0.026) | 0.240 | (0.047) |
| Colombo Classic Vanilla | 0.165 | (0.100) | 0.027 | 0.167 | (0.028) | (0.038) | 0.541 | (0.017) |
| Colombo Classic Blueberry | 0.416 | (0.142) | 0.143 | 1.310 | (0.030) | (0.042) | 0.089 | (0.442) |
| Colombo Classic Peach | 0.238 | (0.147) | -0.091 | 0.057 | (0.035) | (0.021) | 0.275 | (0.089) |
| Colombo Classic Strawberry | 0.252 | (0.171) | 0.276 | -0.123 | (0.034) | (0.018) | 0.226 | (0.289) |
| PL Blueberry | 0.122 | (0.092) | -0.004 | 0.073 | (0.029) | (0.020) | 0.158 | (0.218) |
| PL Cherry | 0.235 | (0.027) | 0.134 | 0.609 | (0.029) | (0.006) | 0.333 | (0.138) |
| PL Peach | 0.107 | (0.200) | 0.065 | 0.100 | (0.042) | (0.016) | 0.410 | (0.225) |
| PL Raspberry | 0.095 | (0.169) | 0.066 | 0.065 | (0.039) | (0.039) | 0.240 | (0.288) |
| PL Strawberry | - | - | - | - | - | - | - | - |

Notes: FOTB = Fruit on the Bottom, LNF = Light & Fit, PL = Private Label

Table C.4: Satiation Estimates – Yogurt

| | $\gamma^*$ | | $a$ | | $\Sigma$ | |
|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD |
| Yoplait Original Strawberry | -0.015 | (0.613) | 1.000 | - | 0.720 | (0.442) |
| Yoplait Original Mountain Berry | -0.072 | (0.821) | -0.077 | (0.034) | 0.652 | (0.314) |
| Yoplait Original Mixed Berry | -0.160 | (1.051) | -0.160 | (0.010) | 0.709 | (0.271) |
| Yoplait Original Key Lime Pie | 0.469 | (0.385) | 0.078 | (0.005) | 0.917 | (0.302) |
| Yoplait Original French Vanilla | 0.246 | (1.477) | 0.012 | (0.014) | 0.369 | (0.498) |
| Yoplait Light Blackberry | 0.218 | (1.748) | 0.050 | (0.002) | 0.447 | (0.481) |
| Yoplait Light Vanilla | 0.956 | (2.289) | 0.096 | (0.014) | 0.799 | (0.481) |
| Yoplait Light Red Raspberry | -2.585 | (1.430) | 0.008 | (0.016) | 1.088 | (0.355) |
| Yoplait Light Blueberry | 0.459 | (0.952) | -0.056 | (0.004) | 0.826 | (0.362) |
| Yoplait Light Peach | -1.250 | (1.936) | -0.251 | (0.020) | 0.194 | (0.418) |
| Dannon FOTB Strawberry | -0.360 | (1.017) | -0.022 | (0.023) | 0.841 | (0.210) |
| Dannon FOTB Blueberry | 0.009 | (1.223) | 0.015 | (0.015) | 0.719 | (0.218) |
| Dannon FOTB Peach | 2.453 | (1.100) | -0.204 | (0.002) | 0.468 | (0.300) |
| Dannon FOTB Mixed Berry | 0.085 | (1.208) | 0.079 | (0.001) | 0.784 | (0.363) |
| Colombo Classic Blackberry | 0.014 | (1.945) | 0.156 | (0.013) | 0.509 | (0.346) |
| Stonyfield Farm Vanilla | 0.734 | (0.527) | -0.166 | (0.017) | 0.811 | (0.400) |
| Stonyfield Farm Strawberry | -0.332 | (1.336) | 0.085 | (0.010) | 0.698 | (0.333) |
| Stonyfield Farm Peach | 0.582 | (0.728) | -0.069 | (0.017) | 0.731 | (0.363) |
| Stonyfield Farm Raspberry | -0.051 | (2.153) | 0.329 | (0.015) | 1.416 | (0.445) |
| Stonyfield Farm Blueberry | -0.997 | (1.160) | 0.002 | (0.018) | 0.426 | (0.411) |
| Dannon FOTB Raspberry | 0.457 | (2.200) | 0.299 | (0.014) | 0.483 | (0.163) |
| Dannon LNF Strawberry Banana | 1.633 | (0.505) | 0.045 | (0.025) | 0.753 | (0.413) |
| Dannon LNF Blueberry | -0.052 | (0.487) | 0.076 | (0.023) | 0.647 | (0.257) |
| Dannon LNF Raspberry | -0.239 | (1.223) | -0.020 | (0.007) | 0.629 | (0.384) |
| Dannon LNF Strawberry | -0.134 | (1.205) | -0.122 | (0.010) | 0.172 | (0.384) |
| Dannon LNF Vanilla | 0.635 | (0.613) | -0.055 | (0.016) | 0.166 | (0.646) |
| Colombo Classic Vanilla | 3.073 | (0.675) | 0.096 | (0.010) | 0.659 | (0.598) |
| Colombo Classic Blueberry | -0.026 | (1.442) | 0.310 | (0.008) | 0.701 | (0.222) |
| Colombo Classic Peach | -0.789 | (1.314) | -0.452 | (0.025) | 1.084 | (0.337) |
| Colombo Classic Strawberry | 0.732 | (1.609) | 0.173 | (0.007) | 0.308 | (0.328) |
| PL Blueberry | 0.025 | (1.166) | -0.253 | (0.020) | 0.358 | (0.362) |
| PL Cherry | 0.058 | (1.220) | 0.002 | (0.014) | 0.826 | (0.423) |
| PL Peach | 0.251 | (1.353) | -0.006 | (0.010) | 1.435 | (0.309) |
| PL Raspberry | 0.955 | (0.312) | 0.011 | (0.019) | 1.021 | (0.421) |
| PL Strawberry | -0.091 | (0.709) | 0.301 | (0.003) | 0.428 | (0.339) |

Notes: FOTB = Fruit on the Bottom, LNF = Light & Fit, PL = Private Label

# D Compensating Value Estimates

Table D.1: Compensating Value – Carbonated Beverage

| | Static | | SSDF1 | |
|---|---|---|---|---|
| | CV | PCV | CV | PCV |
| Pepsi | 0.0195 | 0.0005 | 20.2509 | 0.3491 |
| Diet Pepsi | 0.0160 | 0.0003 | 5.0299 | 0.1465 |
| Mountain Dew | 0.0162 | 0.0003 | 3.9403 | 0.1134 |
| Pepsi CF | 0.0172 | 0.0003 | 3.7450 | 0.1036 |
| Diet Pepsi CF | 0.0161 | 0.0003 | 5.3870 | 0.1380 |
| Wild Cherry Pepsi | 0.0137 | 0.0003 | 6.6039 | 0.1830 |
| Schweppes | 0.0149 | 0.0003 | 8.4965 | 0.2112 |
| Coke CF | 0.0148 | 0.0003 | 11.7279 | 0.2525 |
| Sprite | 0.0155 | 0.0002 | 8.0336 | 0.1667 |
| Diet Coke | 0.0197 | 0.0003 | 8.7617 | 0.2237 |
| Diet Sprite | 0.0151 | 0.0003 | 14.3698 | 0.2753 |
| Diet Coke CF | 0.0170 | 0.0003 | 16.9473 | 0.2852 |
| Cherry Coke | 0.0182 | 0.0003 | 14.4814 | 0.2754 |
| Coke | 0.0184 | 0.0003 | 17.0918 | 0.3034 |
| Barqs | 0.0143 | 0.0004 | 23.3214 | 0.4352 |
| A&W | 0.0161 | 0.0003 | 12.3346 | 0.2435 |
| 7Up | 0.0152 | 0.0003 | 9.7593 | 0.2274 |
| Diet 7Up | 0.0169 | 0.0003 | 8.2013 | 0.1628 |
| Mug | 0.0166 | 0.0003 | 11.1629 | 0.2563 |
| PL Cola | 0.0160 | 0.0003 | 18.5633 | 0.3717 |
| PL Cream Soda | 0.0160 | 0.0003 | 12.4827 | 0.2908 |
| PL Cherry | 0.0163 | 0.0003 | 12.1290 | 0.2267 |
| PL Fruit Punch Soda | 0.0178 | 0.0003 | 7.0369 | 0.1979 |
| PL Ginger Ale | 0.0170 | 0.0003 | 7.2441 | 0.1984 |
| PL Grape | 0.0160 | 0.0003 | 7.5850 | 0.1952 |
| PL Lemon Lime | 0.0151 | 0.0003 | 8.3066 | 0.2016 |
| PL Orange | 0.0171 | 0.0003 | 10.1558 | 0.2423 |
| PL Diet Ginger Ale | 0.0194 | 0.0004 | 17.8160 | 0.3501 |
| PL Diet Orange | 0.0150 | 0.0003 | 15.8729 | 0.3277 |
| PL Root Beer | 0.0155 | 0.0003 | 14.4087 | 0.2485 |

Notes: (1) CF = Caffeine Free, PL = Private Label; (2) The table reports posterior medians.

Table D.2: Compensating Value – Yogurt

| | Static | | SSDF1 | |
|---|---|---|---|---|
| | CV | PCV | CV | PCV |
| Yoplait Original Strawberry | 0.5490 | 0.0230 | 12.4628 | 0.7382 |
| Yoplait Original Mountain Berry | 0.5016 | 0.0208 | 1.6155 | 0.1373 |
| Yoplait Original Mixed Berry | 0.4663 | 0.0175 | 4.7407 | 0.2807 |
| Yoplait Original Key Lime Pie | 0.5364 | 0.0218 | 8.8176 | 0.5082 |
| Yoplait Original French Vanilla | 0.5546 | 0.0186 | 5.5190 | 0.2571 |
| Yoplait Light Blackberry | 0.4779 | 0.0197 | 7.1409 | 0.3615 |
| Yoplait Light Vanilla | 0.4737 | 0.0206 | 7.6276 | 0.4045 |
| Yoplait Light Red Raspberry | 0.4465 | 0.0209 | 4.5683 | 0.1997 |
| Yoplait Light Blueberry | 0.5127 | 0.0205 | 8.5746 | 0.4018 |
| Yoplait Light Peach | 0.4772 | 0.0167 | 6.6978 | 0.2903 |
| Dannon FOTB Strawberry | 0.3911 | 0.0183 | 7.0690 | 0.3511 |
| Dannon FOTB Blueberry | 0.5199 | 0.0212 | 9.1290 | 0.6163 |
| Dannon FOTB Peach | 0.4066 | 0.0164 | 7.7693 | 0.4446 |
| Dannon FOTB Mixed Berry | 0.4875 | 0.0185 | 4.5784 | 0.2852 |
| Colombo Classic Blackberry | 0.4620 | 0.0228 | 5.7094 | 0.3335 |
| Stonyfield Farm Vanilla | 0.4172 | 0.0173 | 9.0676 | 0.7036 |
| Stonyfield Farm Strawberry | 0.4590 | 0.0161 | 9.5513 | 0.5074 |
| Stonyfield Farm Peach | 0.4837 | 0.0189 | 7.6548 | 0.4301 |
| Stonyfield Farm Raspberry | 0.4330 | 0.0206 | 8.0039 | 0.4764 |
| Stonyfield Farm Blueberry | 0.4736 | 0.0222 | 8.3628 | 0.5760 |
| Dannon FOTB Raspberry | 0.5147 | 0.0147 | 9.4719 | 0.5076 |
| Dannon LNF Strawberry Banana | 0.3848 | 0.0178 | 7.5411 | 0.3459 |
| Dannon LNF Blueberry | 0.5130 | 0.0202 | 9.8317 | 0.5973 |
| Dannon LNF Raspberry | 0.5229 | 0.0215 | 12.8920 | 0.6775 |
| Dannon LNF Strawberry | 0.3932 | 0.0175 | 8.6497 | 0.5356 |
| Dannon LNF Vanilla | 0.4636 | 0.0208 | 8.1320 | 0.3287 |
| Colombo Classic Vanilla | 0.6120 | 0.0195 | 6.6391 | 0.3694 |
| Colombo Classic Blueberry | 0.5123 | 0.0153 | 7.0741 | 0.3699 |
| Colombo Classic Peach | 0.5952 | 0.0242 | 9.6205 | 0.5396 |
| Colombo Classic Strawberry | 0.5589 | 0.0247 | 8.7918 | 0.4928 |
| PL Blueberry | 0.5812 | 0.0215 | 7.9742 | 0.4067 |
| PL Cherry | 0.5303 | 0.0181 | 6.5377 | 0.3454 |
| PL Peach | 0.4834 | 0.0150 | 6.3499 | 0.3378 |
| PL Raspberry | 0.5532 | 0.0225 | 8.4701 | 0.5316 |
| PL Strawberry | 0.4818 | 0.0139 | 8.4998 | 0.5472 |

Notes: (1) FOTB = Fruit on the Bottom, LNF = Light & Fit, PL = Private Label; (2) The table reports posterior medians.

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