Identifying and Estimating Brand Satiation Using Purchase Data: A Structural Hidden Markov Modeling Approach

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Abstract

In product categories such as yogurt, cereal and candy, consumers are likely to be satiated after frequent consumption of the same brand, leading to variety-seeking and switching to other brands. Prior research has modeled satiation mostly using consumption and preference data, but most firms have access to only purchase data. Identifying satiation and estimating satiation effect using purchase data remain a significant challenge. We develop a Hidden Markov Model (HMM) based structural approach and identify and estimate satiation using scanner purchase data of yogurt brands. In this model, consumers temporarily stay in an unobserved satiation state. The results show that consumers may be occasionally satiated for a certain brand, and that the satiation probabilities differ significantly across brands. Our model explains and predicts consumer satiation and its effects better than benchmark models.

Keywords: consumer behavior, satiation, brand choice, variety-seeking, structural model, Hidden Markov Model

1. Introduction

In many product categories such as yogurt, cereal and candy, consumers[1] experience satiation effects. Thus, observed brand-switching behavior may not be driven only by variation in brand characteristics or marketing mix, but by satiation after intensive consumption of a brand. A deep understanding of satiation effects and behavior is important for marketing researchers, practitioners, and public policy officials.

For researchers, identifying satiation and estimating satiation effects using purchase data are critical to understand consumer choice behavior. By estimating and quantifying the effect of satiation on consumer brand choice, practitioners can better target consumers and market new or substitute brands to those with a high probability of being satiated. For public policy officials, it is important to understand whether a new brand will bring additional welfare gains and whether these gains will come from new consumers who prefer the new brand or from the rest of the population who may just switch to a new brand because of satiation with the previous brand.

Empirical research on satiation and variety-seeking is mostly based on consumption and preference data. Research in variety-seeking modeling suggests that products may be decomposed into satiable attributes and that the accumulation of such attributes may lead to a high disutility for the currently owned brand and a switch to a new brand (McAlister 1982, Lattin and McAlister 1985, Feinberg, Kahn, and McAlister 1992). In addition, satiable attributes allow for different levels of variety-seeking or reinforcement effects (Lattin 1987). The identification of satiation effects in these models relies on high quality attribute level *consumption* data and *preference* data that may not be readily available for many product categories.[2] Furthermore,

[1] We use consumer(s) and household(s) interchangeably.
[2] Sarigöllü (1998) provides a way to implement Dynamic Attribute Satiation (DAS) models (e.g., McAlister 1982) using choice data. This procedure requires high quality consumption/preference data with a small degree of heterogeneity.

these models ignore possible serial correlations among purchases that could lead to potentially incorrect inferences.

Identifying brand satiation and estimating satiation effects using *purchase* data remains a significant challenge for several reasons. First, satiation is an unobserved phenomenon; consumers' experiences and consumption are difficult to track; and consumers may avoid satiation by changing consumption occasion, consumption time, or consumption order, making it challenging to detect satiation. Second, the existence of multiple serially correlated unobserved factors—especially inertia effects—may 'contaminate' datasets. For example, habitual decision making, rather than conscious decision making, leads to consumers' 'structural state dependence' (Seetharaman 2004, Dubé, Hitsch, and Rossi 2010)—even when consumers are relatively experienced or aware of multiple choice alternatives.[3] Third, consumers are heterogeneous across time. Without appropriate assumptions of the satiation process, product switches may be falsely captured by cross-sectional random effects.

We empirically investigate satiation using purchase data and address the above challenges by allowing unobserved state transitions in conventional choice models. In our dataset, a significant number of consumers exhibit strong back-and-forth switching patterns among different brands. If the frequent switching patterns cannot be well explained by variations in product characteristics and marketing mix ("unexplained" switch), we may infer possible brand satiation.[4] A quasi-experiment, comparing consumers' switching behavior after an "unexplained" switch with that after an "explained" switch confirms the existence of a satiation state. Based on the above

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[3] Much research has focused on distinguishing real from fake inertia based on Heckman (1981) without considering other sources of the unwanted serial correlation (e.g., Dube et al. 2010).

[4] An "unexplained" switch from one brand to another means that both brands are available in the store for two successive periods and that the switch is not due to the following reasons: (a) price discount or coupon from the target brand; (b) price increase by the original brand; and (c) relative price increase of the original brand.

findings, we construct a Hidden Markov Model (HMM), allowing consumers to switch to brand-specific unobserved satiation states. The estimation results show that the model detects structural changes leading to significantly lower brand preference and more frequent switches. In addition, the model results also reveal different satiation probabilities over different brands.

2. Relevant Literature

Consumers care not only about the flavor, ingredients, or other attributes of a brand, but also about the entire brand experience that may lead to satiation. Therefore, brand satiation is important to study. While theoretical and experimental studies provide evidence for satiation and variety-seeking behavior, empirical studies using consumer purchase data find strong inertial effects (e.g., Chintagunta 1999). Most previous studies explain consumer brand switching as the result of variation in observable brand characteristics, marketing mix, or idiosyncratic shocks. A popular specification of brand switching models assumes linear utilities, allowing some measures of state dependence (e.g., lagged choices) to additively enter the utility function to capture inertial effects (Keane 1997, Allenby and Rossi 1998, Chandukala et al. 2008, Dubé, Hitsch and Rossi 2010). Although these specifications are relatively easy to implement, they are restrictive and hard to interpret in different applications. For example, the number of previous periods to be included in such models is an arbitrary decision and negative state dependence coefficients obtained from such models are hard to interpret. Consumers' past behavior may have differing effects on current period purchase and a linear model may not be able to capture both the positive state dependence effect and the negative satiation effect.

A limited number of studies try to model satiation effects or consumer brand switching behavior using nonlinear effects. Baucells and Sarin (2010) introduce an analytic model to address the trade-off between variety-seeking and habitual behavior. Using experimental data, Hasegawa, Terui, and Allenby (2012) estimate a dynamic model where the satiation parameter is a flexible function of time. By estimating individual level parameters using Bayesian methods, the model provides information on consumers' satiation status. Yet, these studies do not offer an empirical solution to purchase data: in the real market environment, additional identification assumptions are needed for a deeper analysis that avoids different sources of serial correlation. Bawa (1990) investigates possible nonlinearity in brand choice by estimating each household's choice sequences; however, consumer cross-sectional heterogeneity may confound the estimation of satiation behavior in his data. In addition, his model makes a strict assumption on how satiation is built based on consecutive purchases. Learning models (Erdem and Keane 1996, Ackerberg 2003, Crawford and Shum 2005, Erdem, Keane, and Sun 2008) suggest that frequent switches across brands may be due to brand trials at the beginning of shopping trips. However, when consumers gain enough experience, their brand choice will "converge" to their favorite brand. These models may not adequately explain the switching pattern among already experienced brands.

A few studies focus directly on forward-looking inter-temporal variety-seeking behavior (e.g., Hartmann 2006). Consumers may switch to a new brand or stop purchasing a brand since the decision to stay with the chosen brand may lead to future disutility. The model in these studies comprises longer lags of previous brand choices additively entering the utility function. Ribeiro (2010) extends this model to a differentiated market with multiple brands. However, Ribeiro's (2010) model makes important assumptions about the outside good and about how consumers' current decisions will affect future decisions. Another loosely related literature comprises structural models proposed by Kim et al. (2002) and Bhat (2005), which use a direct utility approach to model within-period satiation effects. Kim et al. (2002) discuss flavor choices rather than brand switches within a period.

Our study focuses on identifying inter-temporal satiation effects. Table 1 shows the utility specifications for selected relevant studies and how our study compares with those studies. While no study has demonstrated clear empirical evidence of inter-temporal brand satiation using a purchase data set, we perform a difference-in-difference graphic test and utilize the phenomenon of "unexplained" switches in our data set to identify brand satiation. Unlike Bawa (1990), which does not capture inter-temporal effect, we show asymmetric inter-temporal effects and a slower-than-instant recovery rate after an "unexplained" switch. We extend Bawa's model by controlling for heterogeneity and compare the modified model with a model containing a one-period lag state dependence control. Unlike Bawa (1990), we conjecture that brand satiation leads to structural breaks and propose a Hidden Markov Model (HMM), which captures the idea that consumers may stay in an unobserved low state for a while after satiation. Compared with Bawa (1990) and earlier models, our model fits considerably better and reveals additional information on consumers' unobserved satiation states.

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Table 1 about here >

To avoid upward bias, models of state dependence effects usually require a certain level of control for cross-sectional heterogeneity. Keane (1997) allows for random coefficients over observed attributes and state dependence effects, and for a flexible error term that depends on unobserved attributes as well. Seetharaman, Ainslie, and Chintagunta (1999) use a Hierarchical Bayesian approach to study state dependence effects. They allow the coefficients to be normally distributed and to vary with consumer-specific characteristics and category-dependent variables. Dubé, Hitsch, and Rossi (2010) use a finite mixture of normal distributions to capture cross-sectional (non-normal) heterogeneity and obtain similar state dependence results. State dependence effects remain positive within the range of observed periods for these studies. We control for cross-sectional heterogeneity using a simulated likelihood method to calculate both the means and the standard deviations of the preference parameters, which are assumed to be normally distributed.

3. Data

We select yogurt as the category for empirical analysis because yogurt is a perishable good with a short shelf-life and expiration date and yogurts are sold in small packages of one, two or four units. Moreover, consumers are likely to purchase yogurt frequently as they make weekly purchases (Ackerberg 2001). Thus, the yogurt category allows us to investigate satiation using purchase data. We use the IRI panel dataset of yogurt purchases in Eau Claire, Wisconsin and Pittsfield, Massachusetts as the primary dataset (cf., Bronnenberg, Kruger, and Mela 2008). To ensure that we can analyze satiation behavior, we need consumers with a sufficiently long purchase history. To this end, we select consumers with more than 20 shopping trips within a three-year period (2001-2003) to study their switching behavior. A total of 3,081 consumers, with 134,009 weekly choice situations, in the IRI dataset meet this criterion.

The IRI datasets contain 89 yogurt brands and over 700 sub-brands. For example, under the DANNON brand, there exist 17 sub-brands and 139 products with different flavors, package sizes, and ingredients. Ten national brands[5] and private label brands make up 96.5% of the total market sales. Consumers are likely to make choices from those 11 alternatives: 84.12% of the 134,009 choice situations involve a single brand choice and 14.04% involve two different brands. In most of the weeks with two brand purchases, consumers exhibit a clear favorite brand with regard to quantity purchased. Only less than 5% of the total choice situations have brand ties. Therefore, we focus on brand level choice and switch behavior.[6] We do not model quantity directly because we observe only household consumption not consumer consumption for us to infer quantity satiation.

The brand price index we use in the analysis is the store level weekly average price per six liquid ounces of all major products under that brand. Because the IRI dataset provides us with transaction-based price information each week, we can also use it as a measure of the choice availability; we allow the choice sets to vary across different stores and weeks based on the availability of price information. In addition, the IRI data also contain information on private label brands.

The summary statistics for our sample appear in Table 2. Among the ten brands, DANNON, STONYFIELD FARM, YOFARM and YOPLAIT may be viewed as “premier brands” with

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[5] The 10 brands are COLOMBO, BREYERS, DANNON, KEMPS, OLD HOME, STONYFIELD FARM, WELLS DAIRY, YOFARM and YOPLAIT. In the IRI dataset, the firm level corresponds to category “L4.” Different brands can belong to the same corporate group (“L3”). For example, DANNON and STONYFIELD FARM are owned by GROUPE DANONE. Each brand also contains different sub-brands (“L5”).

[6] When a consumer chooses multiple brands in a shopping trip, we use the most frequently chosen brand as the focal brand. In case of a tie, we randomly choose one of the brands available on the shopping trip. Less than 5% of the purchases exhibit ties.

average price indexes higher than 0.6, while KEMPS and PRIVATE brands have the lowest prices. We measure a brand's display by the average share of the weeks with any of the brand's products on display. We measure a brand's feature advertising by the average shares of the weeks with coupons or feature advertisement of any product within that brand. KEMPS, WELLS BLUE BUNNY, and OLD HOME exhibit the highest levels of display or feature in the data.

< Table 2 about here >

Table 3 offers a summary of the brand switching behavior. A total of 58,022 out of 134,009, or roughly 45% shopping weeks involve the purchase of a brand different from the one bought on the previous purchase occasion. YOPLAIT, DANNON and WELLS BLUE BUNNY brands have the lowest switching rate, indicating strong brand loyalty for these brands. To further investigate the source of the brand switches, we consider controlling for changes in relative prices and marketing strategies. We define a brand's relative price in a given time period as the ratio of that brand's price to the average price of the rest of the brands during the same period. If the brand chosen in period t differs from that chosen in period t + 1, we first check for the following possibilities. If the relative price of the brand chosen at t is not greater and the relative price of the brand chosen at t + 1 is not smaller, the brand switch cannot be explained by relative price. Similarly, if a brand switch between period t and period (t + 1) is not due to a feature or coupon of the target brand at period (t+1) or a temporary coupon of the original brand at period t, the brand switch cannot be explained by feature or coupon. When calculating the unexplained switches, we rule out cases when brand price indices are missing to avoid unavailable brands. The sample suggests that even after accounting for relative price changes and promotion changes, about 12.32% of the switches remain unexplained.[7] These unexplained switches may

[7] Notice that the measure of unexplained switches is relatively conservative since it is possible that switches due to satiation coincide with a promotion period. This measure also accounts for brand availability. However, if a switch

be due brand satiation. For example, YOPLAIT has the lowest brand switches, perhaps indicating a stronger brand loyalty; while it has higher-than-average unexplained switches.

< Table 3 about here >

Although we observe several extremely persistent brand choices, switching behavior is not rare across most consumers. The average number of shopping trips during the three-year period is approximately 43 and the average number of brand switches is 20. Figure 1 shows the histogram of total brand switches for the consumers. About 73.52% of the consumers have at least one unexplained brand switch; 10.81% have five or more unexplained brand switches.

< Figure 1 about here >

The unexplained switches are not likely to be driven by differences in household members. About 10.8% of a total of 6,962 switches among the top 10 brands by 418 single member households across 17,172 choice situations cannot be explained by similar observed characteristics, indicating potential preference for variety-seeking. Nor can the switches be completely explained by brand learning. In the first year of the dataset, 584 households experienced at least five brands. For the households with rich experience, we record their unexplained switches to their experienced brands in the following years. For 581 households who have records in the following years, 9.37% (1,089 out of 11,625) of the switches are unexplained switches. In addition, the total number of unexplained switches have a slightly upward trend during the sample period, indicating that brand learning is not the main cause of the phenomenon.

One possible explanation for such "unexplained" switches is satiation effect. In an analysis of household scanner panel data, Bawa (1990) documented "hybrid" consumers, who are affected

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is caused by flavor unavailability, it may be captured as "unexplained." This may be of less concern for more popular brands.

by both positive state dependence and satiation effects. In our dataset, we can examine these effects by investigating individual hazard rate changes. Table 4 shows that 66% of the consumers have non-monotonic hazard rates for shopping runs less than 4; and 10% of the consumers have increasing hazards with high switches per choice.

< Table 4 about here >

To examine how the unexplained switches may capture brand satiation, we compare brand choices before and after an “unexplained” switch with those before and after an “explained” switch. We plot in Figure 2 the factional polynomial fitting curves of the choice probabilities of two global brands (Yoplait and Dannon) 10 weeks before and after the treatments or unexplained switches. Week 0 corresponds to the week of consumer’s shopping trip *next to* the unexplained switch week. Note that the original choice probability in Week -10 is significantly higher in the treatment group than that in the control group ($p < 0.001$) for Yoplait (47% versus 43%) and Dannon (33% versus 28%), favoring a satiation argument. Both the brands show significant decreasing trends toward the unexplained switch treatment; the fitted curve of Yoplait remains flat for the initial two weeks after the treatment; while the fitted curves of Dannon show a more decreasing trend for the same period. Aggregate choice probabilities with “explained” switches provide a test for satiation effect. The unexplained switch treatment leads to an asymmetric recovery, but we do not observe such an asymmetry in the explained switch treatments. For Yoplait brand products, the aggregate choice probabilities start to recover before explained switch treatments and pick up fast to reach their original levels. For Dannon brand products, the corresponding probabilities do not vary significantly before and after the explained treatment; the unexplained switch scenarios also reveal a slow and delayed recovery.

<Figure 2 about here >

On the one hand, such a pattern cannot be picked up by Bawa (1990)'s model. In Bawa (1990), the recovery of satiation is instantaneous[8], and the satiation process is modeled as an opposite yet symmetric effect, which is "triggered" at the peak of a nonlinear (quadratic in consecutive purchases) utility function. The model may underestimate the effect of satiation (with an upward biased satiation threshold); moreover, the satiation threshold may be changing over time, depending on consumers' outside activities and consumption shocks. Thus, a point estimate of the threshold may exhibit false precision.

On the other hand, if the brand switching cost is significant, a consumer may overstay with the original brand until her disutility passes a threshold and the cumulated disutility may prevent consumers from restoring their original preference, resulting in a longer period of satiation effects. This hypothesis indicates that satiation, unlike habit, is more likely to affect consumers' utilities discontinuously, leading to a structural break.

The downward trending choice probabilities in Figure 2 before the treatments may suggest that the satiation process happens before an unexplained switch. We provide another comparison of the number of brands chosen before and after the potential "treatments." Figure 3 demonstrates the differences between the two major brands in the markets. Notice that we include switches (unexplained or explained) in the "before" category, so it is expected that the number of brand choices *before* should be more than the number of brand choices *after* by construction. However, in the unexplained condition groups, we can see that brand choices are higher. Overall, the variety levels of brand choices in unexplained switch conditions are significantly higher ($p < 0.001$) than their counterparts. Although "unexplained switches" do not

[8]The author argues that the assumption is consistent with the intervention of the switch and low consumer involvement.

tell us when a satiation process starts, we see strong evidence that they are associated with brand satiation.

<Figure 3 about here >

In the next section, we first describe conventional approaches used to capture state dependence and satiation; then we investigate the phenomenon using structural modeling approach. If our structural break hypothesis of satiation is true, a Hidden Markov Model may flexibly capture the cross-time preference change, especially when satiation thresholds vary over time and are hard to capture. We introduce the HMM to capture any potential structural break due to satiation.

4. Model Development and Estimation

4.1. Standard Mixed Logit as a Benchmark Model

Conventional approaches considering state dependence effects typically assume that previous purchases directly affect choice utility. These model specifications involve versions of mixed logit with lagged choice-specific variables. For example, in a common utility setting, consumer h's utility for brand k at week t u_{kht} can be written as:

$$\mathrm{u_{hkt}} = Q_{hk} + \alpha_h Price_{kt} + \gamma_h f(y^{hkt-1}) + \beta_h X_{kt} + \epsilon_{hkt}, \quad (1)$$

where Q_{hk} is the base utility of consumer h for brand k, $Price_{kt}$ is the price of brand k at time t, $\mathrm{f}(\mathrm{y}^{\mathrm{hkt}-1})$ represents the previous state, γ_h can flexibly capture the effects of state dependence. For example, in a common setting, $\mathrm{f}\left(\mathrm{y}^{\mathrm{hkt}-1}\right) = I(y_{hkt-1} = 1)$; alternatively, it can consist of the discounted sum of all previous choices. X_{kt} is the set of marketing covariates of brand k at time t, ε_{hkt} is an error term, α, β, and γ are parameters.

Bawa (1990) points out a nonlinear pattern for state dependence effect. A modified version of Bawa's model for utility u_{hkt} of consumer h consuming brand k at time t with controls for cross-sectional heterogeneity and covariates can be written as:

$$u_{hkt} = Q_{hk} + \alpha_h Price_{kt} + \gamma_{1h} B_{hkt} + \gamma_{2h} B_{hkt}^2 + \beta_h X_{kt} + \epsilon_{hkt}, \quad (2)$$

where B_{hkt} represents the cumulative consumption of consumer h of brand k and the other terms are as defined earlier. A significantly negative γ_{2h} indicates the presence of a "hybrid" behavior, possibly caused by the coexistence of inertia and satiation effects. Moreover, a satiation threshold can be estimated using the estimated peak of the functional form in B.

Even Bawa's (1990) specification with the addition of controls for heterogeneity and covariates cannot capture the phenomena that households may remain satiated for a while and switch more frequently during that period. To capture unobserved satiation states, we test an HMM, where we model brand choices as emission probabilities with consumers falling into unobserved states of satiation from time to time.

4.2. Markov Chain Transition Matrix

We assume that consumers may switch from a normal state to a satiation state for different brands or switch back. This gives us a sparse transition matrix in Table 5, where the row elements represent the probability of switching from the row state to the column state, $P_{ij} = P(s_t = j | s_{t-1} = i)$, and elements in each row add to one, $\sum_j P_{ij} = 1$. There are a total of 12 states, corresponding to one normal state and 11 brand-dependent states. Consumers may be satiated with any of the brands. In our setting, consumers do not switch directly from one satiation state to another; instead, they only switch between the normal state and each brand-dependent state. This setting greatly reduces the number of parameters and also reflects the idea that the satiation process is most likely to be determined by consumers' top brand choices.

< Table 5 about here >

We model the non-zero transition probabilities using logit probabilities. The propensity of switches between the states depends on the parameter $c_{\mathrm{state,state}}$:

$$P_{N,j} = \frac{\exp(c_{Nj})}{1+\sum_{j=1}^{11}\exp(c_{Nj})}, \forall \ j \in \{N, S1, \ldots, S10\} \tag{3}$$

$$P_{N,S11} = \frac{1}{1+\sum_{j=1}^{11}\exp(c_{Nj})} \tag{4}$$

$$P_{s,s} = \frac{\exp(c_s)}{1+\exp(c_s)} \ \ \forall \ \ s \in \{S1, \ldots, S11\} \tag{5}$$

$$P_{s,N} = 1 - P_{s,s} \ \ \forall \ \ s \in \{S1, \ldots, S11\}, \tag{6}$$

where parameters involve constant terms $C = \{c_{NN}, c_{N1}, \ldots, c_{N9}, c_1, \ldots, c_{10}\}$ which capture the average state transition probability.

4.3. State-dependent Choice Distribution

To capture preference changes in different states, we assume that each consumer h in period t has the following utility specification for choice alternative k:

$$U_{hkt}^{\mathrm{state}} = Q_{hk}^{state} + \alpha_h Price_{kt} + \boldsymbol{\beta_h} X_{kt} + \epsilon_{hkt}, \tag{7}$$

$$u_{h0t} = 0;$$

where $\{Q_{hk}^{state}\}_{k=1}^{K}$ is the state-specific intrinsic utility (unobserved fixed effect) of brand k. In the normal state, consumers have intrinsic utility $\{Q_{hk}^{N}\}_{k=1}^{K}$, while in each brand-dependent state j, consumers have a different intrinsic utility $Q_{hj}^{S_j}$ for the brand j. If brand satiation causes a consumer to switch away from brand j, we expect the intrinsic utility $Q_{hj}^{S_j}$ to be significantly lower. This setting gives us a total of K+J state related parameters, where K is the total number of choices and J is the total number of states specified. X_{kt} captures marketing covariates, including supermarket displays and advertisements. u_{h0k} represents the outside choice. Under the standard extreme value distribution assumption on the error term ϵ_{hkt}, the conditional choice probability of a consumer h choosing brand k in period t can be written as:

$$P(Y_{hkt} = 1 | \text{state}, \alpha_{hk}, \boldsymbol{\beta_{hk}}, Q_{hk}) = \frac{\exp\left(u_{hkt}^{state}(\alpha_{hk}, \boldsymbol{\beta_{hk}}, Q_{hk})\right)}{1+\sum_{k'} \exp\left(u_{hk't}^{state}(\alpha_{hk}, \boldsymbol{\beta_{hk}}, Q_{hk})\right)} \quad (8)$$

To flexibly control for heterogeneity, we further assume that each of the coefficients $\alpha_{hk}, \boldsymbol{\beta_{hk}}, \{Q_{hk}\}_{k=1}^{K}$ is normally distributed. Thus, the aggregate state-dependent choice probability can be written as:

$$P(Y_{ht} = k | \text{state}) = \int_{\alpha} \int_{\boldsymbol{\beta}} \int_{\{Q\}} \frac{\exp\left(u_{hkt}^{state}(\alpha_{hk}, \boldsymbol{\beta_{hk}}, Q_{hk})\right)}{1+\sum_{k'} \exp\left(u_{hk't}^{state}(\alpha_{hk}, \boldsymbol{\beta_{hk}}, Q_{hk})\right)} dF(\alpha_{hk}, \boldsymbol{\beta_{hk}}, \{Q_{hk}^{state}\}) \quad (9)$$

4.4. Estimation and Parameter Choices

Combining Equations (1)-(9) and given proper initialization, the likelihood function for each consumer can be defined as:

$$\log \mathcal{L}_h = \sum_{t=1}^{T} [log \sum_{i=1}^{I} P(Y_{ht} | state_{ht} = i) P(state_{ht} = i | \mathcal{F}_{ht-1})] \quad (10)$$

where $\mathcal{F}_{ht-1}$ represents the information for consumer h, at period $t-1$. Since the state variable is not observed, we proceed by applying a nonlinear recursive filter. Given filtering probability $P(state_{ht-1} | \mathcal{F}_{ht-1})$, we calculate:

$$P(state_{ht} = j | \mathcal{F}_{ht-1}) = \sum_i P(state_{ht} = j | state_{ht-1} = i) P(state_{ht-1} = i | \mathcal{F}_{ht-1}), \quad (11)$$

Once Y_{ht} is observed, the filtering probability is updated using the Bayes' formula:

$$P(state_{ht} = j | \mathcal{F}_{ht}) = P(state_{ht} = j | \mathcal{F}_{ht-1}, Y_{ht}) \quad (12)$$

$$= \frac{P(state_{ht}=j, Y_{ht}|\mathcal{F}_{ht-1})}{P(Y_{ht}|\mathcal{F}_{ht-1})} \quad (13)$$

$$= \frac{P(Y_{ht}|state_{ht}=j, \mathcal{F}_{ht-1})P(state_{ht}=j|\mathcal{F}_{ht-1})}{P(Y_{ht}|\mathcal{F}_{ht-1})} \quad (14)$$

By iterating between the above two equations, filtered probability and the simulated likelihood for each consumer can be readily calculated, which can be written as:

$$\log \mathcal{L} = \frac{1}{RH} \sum_r^R \sum_h^H \sum_{t=1}^T [log \sum_{i=1}^I P(Y_{ht}|state_{ht} = i, \Theta_h^r) P(state_{ht} = i|\mathcal{F}_{ht-1})] \quad (15)$$

In practice, we reduce the parameters to be estimated from the transition matrix by focusing on the two brands with the highest market shares, Yoplait and Dannon. For the remaining brands, we estimate a common switching probability. Therefore, the parameters to be estimated in the transition matrix become $P_{NN}, P_{NY}, P_{ND}, P_{YY}, P_{DD}, P_{OO}$, where "N" stands for the normal state; "Y" and "D" stands for the satiation (state dependence) state for Yoplait and Dannon; "O" represents other brands (see Table 6).

< Table 6 about here >

Similarly, we focus on the changes of the average brand fixed effects for Yoplait and Dannon given different states, and reduce other fixed effects at their corresponding satiation states to one parameter ($Q_{hk}^{S_k} = Q_{h,other}^{S_{other}}$ for all k if k is not Yoplait or Dannon). Compared with a benchmark model of a simple mixed logit model with lagged state variable (two additional parameters capturing state dependence effects) and Bawa's quadratic utility function with mixed coefficients (four additional parameters capturing state dependence effects), our proposed HMM has nine additional parameters governing transition matrix and the conditional brand fixed effects. The model specifications to be tested appear in Table 7.

< Table 7 about here >

Our primary sample for model estimation consists of consumers who frequently purchased yogurt products. In 2003, 817 consumers (27% of the original sample) had number of shopping trips greater than or equal to 20. A10% random draw (82 consumers) was made from the processed data set and our main results are based on this sample. To test the robustness of the satiation effect, another sample of 96 consumers with high numbers of Yoplait or Dannon purchases was also drawn from the 817 consumers. The sample was drawn in such a way that we could estimate the model with three unobserved states: the normal state, the state with brand satiation on Dannon, and the state with brand satiation on Yoplait. Because the latter sample is more homogenous, it may give us a more clear-cut result under the single transition matrix. The estimation results of the three-state-model appear in the Appendix (

Table **13**, Table 14, and Table 15). For all our estimations, we use 500 independent draws for each consumer and each random coefficient. We report the means and the relevant standard deviations of the coefficients in the next section.

5. Results and Discussion

We first present the estimation results of the linear model in Table 8. Columns Model 1a and 1b list the estimation results for a simple mixed logit model with a one period lagged choice dependence variable, while Columns Model 2a and 2b provide the results for a model incorporating a quadratic term for consecutive purchases, similar to Bawa (1990).

< Table 8 about here >

The results show that the price coefficients have the expected sign and are consistent across models. Brand fixed effects imply similar preference rank and heterogeneity information. The global brands, Yoplait and Dannon, are significantly more preferred. Marketing covariates play important roles in consumers' brand choice. For example, marketing variables tend to reduce the brand fixed effects and explain much of the heterogeneity in the state dependence effects.

The parameters γ and γ_2 capture consumer inertial effects. For example, in Column Model 2b, the parameter γ implies that if an average consumer purchased a brand only in the last period, her utility will increase by 0.28 points on average. Equivalently, this consumer is indifferent to a 4.4 cent price increase in the next period if she has purchased the item only in the last period. This inertial effect will increase over time as she continues choosing the brand before reaching a "threshold." Around the threshold (five consecutive purchases of a brand), her utility of the brand will have increased by 12.8 cents on average and will then slowly drop thereafter.

Compared with Models 1a and 1b, the mixed logit versions of Bawa (1990) suggest that major consumers in the sample are consistent with the hybrid type who are subjected to inertial effects first and then satiation effect after certain consecutive consumption level. The additional coefficients estimated provide useful information on each consumer's "satiation threshold," or the number of consecutive periods that each consumer would go through before a drop in the brand-specific utility.

According to the estimates in Model 2b, the average satiation threshold is about five consecutive purchases with values ranging from two to positive infinity. Therefore, the modified Bawa model captures within household heterogeneity by adding the quadratic term. However, although the quadratic mixed logit model provides information on the satiation thresholds, it rarely improves the model fit. An average consumer is not likely to trigger satiation often since the dataset (less than 5% of the sample) has only a few consecutive runs longer than five.

Model 2 defines satiation as a phenomenon after consecutive purchases with brand utility renewing instantly after a brand switch. However, our empirical evidence suggests that consumers stay in the satiation state for a longer time, leading to potentially more frequent switches. Using only pervious consecutive purchases is not sufficient to separate potentially unobserved inertial and satiation states. The consumer behavior literature also views the recovery of satiation as a nontrivial question (Hetherington et al. 2006, Galak et al. 2009). Therefore, using the HMM, we are able to relax the instant recovery assumption and allow consumers to stay in unobserved states for a longer period of time.

Table 9 shows the estimation results in the “normal” state, where the brand fixed effects have similar rankings compared with those from the mixed logit models. However, consumers may stay in alternative states for differing periods of time. In Table 10, we show the two alternative states for Yoplait and Dannon. The estimates indicate that in their alternative states, preferences for Yoplait and Dannon are significantly lower, reducing the likelihood of choice of these brands. Moreover, from the switching parameters shown in Table 10 and 11, we can calculate the probabilities of staying satiated in the steady states. Consumers are about two times more likely to stay in the satiation state of brand Dannon compared with that of Yoplait (14.48% versus 7.86%). State dependence probabilities p_{YY} and p_{NN} significantly differ from each other with more consumers likely to remain satiated with Dannon than Yoplait, given previous satiation state. This is consistent with the graph test in Figure 2, where the choice probabilities for Dannon reduce further after an unexplained switch. The heterogeneous brand level satiation patterns imply that consumers may have different optimal consumption rates for each brand, and marketers should take into account the unstable preferences for different brands. In particular, considering that the brand fixed effects for Yoplait and Dannon are similar in the normal state, the differential satiation effects may imply that either consumers have different perceptions of these two brands or that these two brands have some important unobserved differences. For example, consumers may view Yoplait more as a credence good like Vitamin supplements so that they can endure a long consumption tenure. Ingredients of Yoplait may also be less satiable with unique features. The switching probabilities from the normal state ($\mathrm{P}_{\mathrm{NX}}, X \in \{N, D, Y\}$) are mostly insignificant. This is probably because consumers are heterogeneous and each consumer does not have enough variations across all brand choices. That is, most consumers switch among different subsets of the brands.[9]

< Table 9, 10, 11 about here >

From Table 12, we can observe that our models' likelihood values are much greater than their benchmarks, underscoring their superior model fit. The improvement comes from the satiation states, which are not only governed by consecutive purchases, but also a slow recovery period. Compared with a satiation threshold argument, the HMM provides a more realistic way to capture the satiation phenomenon as the results show that the threshold values estimated in the previous models are too high and very few consumers have chances of triggering them.

< Table 12 about here >

Our model may be used for specific subsamples with slight modifications in the transition matrix. For example, if a researcher is interested in the satiation of certain brands, she may narrow her sample to only consumers with frequent consumption of those brands. In such cases, the transition matrix can be further simplified with a more homogenous consumer pool. In the Appendix, we consider a subsample of purchasers with frequent records on Yoplait and Dannon products (See Appendix

Table **13**, Table 14, and Table 15). In this group of customers, we expect strong satiation effects for Yoplait and Dannon and specify a HMM of three hidden states (normal, satiation state

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9 In the Appendix, we provide a similar estimation for a more focused group of Yoplait and Dannon purchasers. Such an estimation provides more clear-cut information on the normal states.

for Yoplait, and satiation state for Dannon). One of the questions researchers/ firms can ask is whether those loyal consumers switch to other yogurt brands (brand satiation) or outside goods (product satiation). This is equivalent to testing in this smaller sample if consumers in the satiation states generally have a lower probability of purchase. Our estimation shows that in such a sample of 96 households, an additional parameter for the outside good in the satiation state is not significant ($p > 0.10$). Therefore, these consumers did not significantly lower the purchase rates of their current brand during the satiation period consistent with a brand satiation story.

6. Conclusion, Implications, Limitations, and Extensions

6.1. Conclusion

In this paper, we addressed the challenge of identifying and estimating satiation using only purchase data. We examined consumer switching patterns for a non-durable experience good using a structural HMM model estimated using scanner purchase data. Although there is significant inertial brand choice in the data, our HMM model results showed that consumers are likely to be satiated under intense consumption and that consumers transition between inertial and satiation states rather than follow a satiation threshold. The satiation effects we identified are robust after controlling for cross-sectional heterogeneity and marketing covariates.

We significantly extend Bawa (1990)'s work that relies on consecutive purchases and instant recovery by showing that satiation can be a broader phenomenon, identified by "unexplained switches" and frequent switch-backs. After an "unexplained switch," consumers' choice probabilities do not pick up instantly compared with choice probabilities after an "explained switch." Our structural HMM results show that satiation effects are asymmetric for different brands.

The evidence suggests that an estimate of satiation threshold relying on consecutive purchases may lead to false precision. This concern can be aggravated when consumers have persistent shopping choices for unknown reasons since the likelihood function will be penalized for every incremental consecutive purchase. The HMM does not enforce consecutive purchases, allowing flexible ways of accumulating consumption. The model exhibits a significantly superior fit than benchmark models with only a reasonable increment in the number of parameters. Instead of reporting a threshold, the HMM shows consumers’ switching characteristics among different unobserved states as well as the probability of staying in each satiation state for each brand. We found that consumers are significantly less likely to remain satiated with Yoplait, compared with Dannon. The heterogeneity across brands suggests that consumers’ preference of brands can lead to differential satiation processes. In the yogurt market, the mean brand preferences do not significantly differ between Yoplait and Dannon in the normal states, yet preference for Dannon deteriorates more steeply than that for Yoplait in the satiation state. Consumers’ perceptions of a brand’s health benefits may affect or overcome the satiation process. This explanation can be compelling especially for an experience food category such as yogurt because the quality of food may not be simply revealed by repetitive consumption. Satiation can be mitigated if a consumer believes in the products’ function over experience.

6.2. Implications

In terms of product targeting, managers could use more customized marketing campaigns depending on the specific category or market under investigation. An important takeaway is that brand satiation is a significant behavioral effect that has been overlooked in previous empirical research due to the domination of positive state dependence. Firms should reconsider their individual marketing strategies and alter them after identifying and estimating satiation effects.

Our model offers a new way to leverage purchase history in modeling consumer choice and making brand promotion decisions. Compared with existing models, our model provides a relatively simple way to utilize less detailed purchase data. Using our model, managers can anticipate which consumers might be satiated when and plan their promotions accordingly.

Managers could also use our model to better predict consumers' unexplained switching behavior than other models. Most structural models explain switching behavior using independent random errors, while our satiation model reveals the hidden state in which a consumer may be and the probability to transition to another state, helping to better predict her switch to alternative brands. This information may be used to improve direct marketing practices. If firms can better target satiated consumers, they can satisfy consumers by offering a greater choice of brands or sub-brands. Armed with the additional information on consumers' satiation, firms can adjust promotions and direct marketing strategies suitably.

Our model reveals the true effects of state dependence and satiation. Using the estimates of these effects, managers can better decide the maximum limit of price increase acceptable to their customers. For example, in our data, an average consumer may tolerate a price increase of 3.6 cents on the brand she owns before switching to a new brand.

From consumer and welfare standpoints, our structural HMM model of satiation and its results suggest that more choice options are preferable in categories where consumers experience satiation. The availability of multiple brands in a category allows for increased consumer utility even as consumers become satiated with the brands they use. Aggregating the increased utility across consumers, we can derive enhanced consumer welfare. Thus, identifying and estimating consumer satiation may explain the continued expansion of many product categories with an increasing array of brand choices and options.

6.3. Limitations and Extensions

Our study has limitations that could lead to more promising research in the future. First, the datasets offer limited information on firms' marketing strategies and consumers behavior. For example, in the IRI dataset, we have limited weekly store-level product information, necessitating assumptions of consumers' observed choice set and characteristics. If more details are available, we could also examine the effects of satiation on consumer responsiveness to marketing strategies. Second, although we focus on demand side estimation, supply side issues related to satiation behavior are also interesting to study. While these issues are beyond the scope of this paper, they could be addressed by future studies. Third the study may be extended to other categories or markets where satiation is prevalent.

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Table 1. Comparison of our Study with Selected Related Studies

Utility/Preference specification	Rationale	Features	Paper
$DAS_{jt} = -\sum_k \beta_k \left[\left(I_{tk} + X_{jk}\right) - \widehat{X}_j\right]^2$	DAS represents preference for choice j, which is decomposed into k attributes. Satiation is attribute-based and consumers are assumed to cumulate attribute inventory over time.	Purchase data: No Inter-temporal Effect: Yes State Dependence: No Variety Seeking: Yes Satiation Effect: Yes	McAlister (1982)
$\rho^{i}_{j\vert j'} = \pi_j - V_i S^{i}_{jj'}$	Conditional preference, $\rho^{i}_{j\vert j'}$ consists of unconditional preference and a discounted satiation component, which is modeled as a first-order Markov process.	Purchase data: No Inter-temporal Effect: Yes State Dependence: No Variety Seeking: Yes Satiation Effect: Yes	Lattin and McAlister (1985); Feinberg et al. (1992)
$U_{ijt} = \left(W_{ij} + V_i S_{ijt}\right) + \sum_k (w_{ik} + v_{ik} s_{ikt}) x_{jk}$	Utility allows discounted satiation over product j and over characteristics k of j. The satiation function depends on the last shopping occasion.	Purchase data: No Inter-temporal Effect: Yes State Dependence: Yes Variety Seeking: Yes Satiation Effect: No	Lattin (1987)
$U(j\vert r_j) = c_j + \beta\gamma_j + \beta_2\gamma_j^2$; $U(j'\vert r_j) = c_{j'}$; where γ_j represents consecutive occasions related to choice j	With $\beta > 0$ and $\beta_2 < 0$, the model captures hybrid consumers who are initial affected by inertial effects more and later dominated by satiation.	Purchase data: Yes Inter-temporal Effect: Yes State Dependence: Yes Variety Seeking: Yes Satiation Effect: Yes	Bawa (1990)
$U_{ijt} = C_{ij} + \alpha_i P_{jt} + \gamma_{1i} I\left(y_{ijt-1} = 1\right) + \gamma_{2i} I\left(y_{ijt-1} = y_{ijt-2} = 1\right) + \cdots + X_{ijt}\beta_i + \epsilon_{ijt}$	With flexible controls for heterogeneity, a positive γ indicates a structural state dependence.	Purchase data: Yes Inter-temporal Effect: Yes State Dependence: Yes Variety Seeking: No Satiation Effect: No	Allenby and Rossi (1998); Dubé, Hitsch and Rossi (2010)
$U_{ijt} = C_{ij} + \alpha_i P_{jt} + \gamma_i \left(\frac{1}{\sum_{\tau}^{t-1} y_{ij\tau} + 1}\right) + \epsilon_{ijt}$	Allows a nonlinear curve of previous choices: consumers gradually learn the true brand experience value.	Purchase data: Yes Inter-temporal Effect: Yes State Dependence: Yes Variety Seeking: Yes Satiation Effect: No	Erdem and Keane (1996); Ackerberg (2003)
$U(x_1, \dots, x_T) = \sum_1^T v(y^{t-1} - r^{t-1} + x_t) - v(y^{t-1})$, $where\ \ y^t = \gamma(y^{t-1} - r^{t-1} + x_{t-1})$; $\mathrm{r}^{\mathrm{t}} = r^{t-1} + \alpha(x_{t-1} - r^{t-1}); y^1, r^1\ \ given$	Consumer's total incremental utility is defined by cumulative consumption, adjusted by habit level. γ captures the satiation effect and α is the habit formation parameter.	Purchase data: No* Inter-temporal Effect: Yes State Dependence: Yes Variety Seeking: Yes Satiation Effect: Yes	Baucells and Sarin (2010)
$U_{i0t} = f(y^{t-1}, \epsilon_{i0t})$ $U_{ijt} = C_{ij} + \alpha_i P_{jt} + \gamma_{1i} I\left(y_{ijt-1} = 1\right) + \epsilon_{ijt}$	Waiting generates more utility after continued purchases of the same brand.	Purchase data: Yes Inter-temporal Effect: Yes State Dependence: Yes Variety Seeking: Yes Satiation Effect: No	Hartmann (2006); Ribeiro (2011)
$U_{ijt} = C_{ij}^s + \alpha_i P_{jt} + x_{jt}\beta + \gamma_i I\left(y_{ijt-1} = 1\right) + \epsilon_{ijt}$, where C_{ij}^s capture brand fixed effects at different states	Consumers may switch back-and-forth among different states, inertial and satiation states, which can be captured by a structural model with an underlying Hidden Markov Model (HMM).	Purchase data: Yes Inter-temporal Effect: Yes State Dependence: Yes Variety Seeking: Yes Satiation Effect: Yes	Our Paper (2017)

Table 2. Summary Statistics: Eau Claire and Pittsfield Markets

Brand	Price	Std. Dev.	Min	Max	Display	Feature
COLOMBO	0.55	0.13	0.20	0.79	23.90%	33.82%
BREYERS	0.50	0.12	0.16	0.80	6.72%	12.95%
DANNON	0.61	0.18	0.10	1.38	17.35%	39.76%
KEMPS	0.45	0.12	0.09	1.30	68.51%	70.49%
OLD HOME	0.49	0.09	0.15	0.83	64.45%	63.26%
STONYFIELD FARM	0.65	0.18	0.24	1.50	26.85%	41.96%
WELLS DAIRY	0.52	0.07	0.34	0.93	75.82%	75.60%
YOFARM	0.70	0.15	0.40	0.85	16.67%	21.93%
YOPLAIT	0.69	0.17	0.24	2.00	16.45%	41.35%
PRIVATE	0.41	0.14	0.13	1.71	16.34%	31.14%

Notes: Price is the average transaction price per six ounce of yogurt. Display is the average share of the shopping trips in which at least one item of the brand is on display. Feature is the average share of the shopping trips in which at least one item of the brand is part of a feature advertisement.

Table 3. Summary Statistics 2: Eau Claire and Pittsfield Markets

Brand	Choice	Brand switches		Unexplained	
COLOMBO	13,299	7,288	54.80%	814	11.17%
BREYERS	5,802	3,702	63.81%	485	13.10%
DANNON	32,912	14,713	44.70%	1798	12.22%
KEMPS	6,904	3,593	52.04%	371	10.33%
OLD HOME	5,538	2,781	50.22%	319	11.47%
STONYFIELD FARM	5,832	2,751	47.17%	347	12.61%
WELLS DAIRY	3,474	1,404	40.41%	211	15.03%
YOFARM	3,503	2,100	59.95%	404	19.24%
YOPLAIT	42,222	14,378	34.05%	1836	12.77%
PRIVATE	10,283	5,312	51.66%	565	10.64%
Total	134,009	58,022	44.71%	7,150	12.32 %

Notes: 1. Outside good choices are not listed.

2. A “Brand switch” is defined as the number of times consumers switch away from a brand chosen on the previous purchase occasion.
3. An “unexplained” switch means that both brands are available in the store for consecutive periods and that the brand switch is not due to any of the following reasons: discount by the new chosen brand; relative price increase of the original brand.

Table 4. Consumer Purchase Hazard at Aggregate and Individual Level

	Run length=1	Run length=2	Run length=3	Avg trips	SPC	# of cases
Aggregate Brand Hazard	0.62	0.45	0.42	44.80	0.46	2587
Hazard (Decreasing)	0.66	0.48	0.16	50.40	0.45	644
Hazard (Increasing)	0.60	0.71	0.92	40.10	0.59	246
Hazard (Non-Monotonic)	0.61	0.39	0.45	43.30	0.45	1697

Notes: Brand Hazard at Run length "L" is defined as the ratio between number of cases that a consumer stops at the Lth consecutive purchase and number of cases that a consumer makes L or more than L consecutive purchases. The table shows that 10% of the consumers may have increasing hazard rate.

Table 5. Full Transition Matrix

	N	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
N	q_{11}	q_{12}	q_{13}	q_{14}	q_{15}	q_{16}	q_{17}	q_{18}	q_{19}	q_{110}	q_{111}	q_{112}
S1	q_{21}	q_{22}	0	0	0	0	0	0	0	0	0	0
S2	q_{31}	0	q_{33}	0	0	0	0	0	0	0	0	0
S3	q_{41}	0	0	q_{44}	0	0	0	0	0	0	0	0
S4	q_{51}	0	0	0	q_{55}	0	0	0	0	0	0	0
S5	q_{61}	0	0	0	0	q_{66}	0	0	0	0	0	0
S6	q_{71}	0	0	0	0	0	q_{77}	0	0	0	0	0
S7	q_{81}	0	0	0	0	0	0	q_{88}	0	0	0	0
S8	q_{91}	0	0	0	0	0	0	0	q_{99}	0	0	0
S9	q_{101}	0	0	0	0	0	0	0	0	q_{1010}	0	0
S10	q_{111}	0	0	0	0	0	0	0	0	0	q_{1111}	0
S11	q_{112}	0	0	0	0	0	0	0	0	0	0	q_{1212}

Table 6. Simplified Transition Matrix for Estimation

	N	Y	D	O1…O9	
N	q_{NN}	q_{NY}	q_{ND}	q_{NO}	q_{NO}
Y	q_{YN}	q_{YY}	0	0	0
D	q_{DN}	0	q_{DD}	0	0
O1	q_{ON}	0	0	q_{OO}	0
…	…	…	…	…	…
O9	q_{ON}	0	0	0	q_{OO}

Notes: The above table shows one of the possible ways to simplify the transition matrix. In the Appendix, we estimate a similar model using only Yoplait and Dannon purchasers so that the transition matrix only consists of the first three states.

Table 7. Models to be Compared

Without Covariates (Control Variables)			With Covariates (Control Variables)		
Model1a	Model2a	Model3a	Model1b	Model2b	Model3b
Simple Mixed Logit	Bawa's Model with Mixed Effects	Hidden Markov Model	Simple Mixed Logit	Bawa's Model with Mixed Effects	Hidden Markov Model

Table 8. Estimation Results of Linear Model

	Without Covariates				With Covariates			
	Model 1a		Model 2a		Model 1b		Model 2b	
A	-6.57	1.809	-7.25	1.698	-6.81	2.324	-6.38	2.200
	0.2821	0.1053	0.3194	0.1034	0.3211	0.1149	0.3138	0.1013
Q1	1.118	1.733	0.761	1.298	0.331	1.044	-0.26	1.767
	0.2235	0.1581	0.2488	0.1298	0.2446	0.1052	0.2224	0.1139
Q2	0.281	1.234	0.192	1.159	-0.15	0.953	-0.60	0.990
	0.2518	0.163	0.2669	0.1955	0.2407	0.118	0.2384	0.136
Q3	3.347	1.295	2.869	0.922	2.000	1.353	1.869	1.182
	0.2358	0.1042	0.2187	0.0884	0.2592	0.0913	0.2307	0.0885
Q4	-1.46	3.006	-1.90	3.446	-2.16	4.265	-1.36	2.196
	0.7186	0.4908	0.5021	0.3632	0.6821	0.5781	0.2688	0.1492
Q5	1.532	0.952	1.606	0.751	1.294	1.458	0.461	1.689
	0.3573	0.2566	0.2963	0.1617	0.3568	0.2441	0.373	0.2042
Q6	1.228	2.060	0.729	1.844	-0.11	2.167	-0.42	2.467
	0.3189	0.2292	0.3149	0.1703	0.3527	0.2346	0.3214	0.2053
Q7	1.644	1.206	1.348	1.420	0.650	1.346	0.552	1.586
	0.3303	0.1938	0.3671	0.1987	0.3948	0.2095	0.3491	0.2062
Q8	-2.07	3.805	-0.98	3.023	-2.58	3.446	-0.47	1.500
	0.5507	0.3643	0.447	0.2983	0.7205	0.4438	0.3344	0.1981
Q9	3.075	1.343	3.057	1.534	2.500	1.429	1.855	1.958
	0.2763	0.1097	0.2376	0.1144	0.2598	0.1294	0.2505	0.1162
Q10	0.120	1.659	0.286	1.655	-0.54	1.807	-0.47	1.950
	0.2822	0.1355	0.2065	0.1023	0.2593	0.1278	0.2109	0.1275
Q11	-1.15	1.621	-1.12	1.704	-0.97	1.306	-1.94	1.942
	0.368	0.1864	0.3117	0.1661	0.3016	0.1506	0.3684	0.2514
Γ	0.368	0.287	0.289	0.042	0.381	0.037	0.314	0.024
	0.0692	0.076	0.055	0.0372	0.0649	0.0999	0.0546	0.0308
γ_2			-0.03	0.018			-0.03	0.014
			0.0105	0.0078			0.0099	0.0065
β_2					0.136	0.030	0.176	0.485
					0.0774	0.1119	0.0802	0.0685
β_3					0.214	0.420	0.317	0.580
					0.0661	0.0471	0.0780	0.0715
Neg LogL	5461.7		5449.44		5421.69		5411.36	

Table 9. HMM Parameter Estimates in the Normal State

	Without Covariates		With Covariates	
α	-8.9459	3.1665	-7.8845	2.7988
	0.4188	0.2003	0.3936	0.1427
Q1	0.7883	1.4986	0.3622	1.8926
	0.234	0.1609	0.286	0.2099
Q2	-0.6843	1.7034	-0.5072	1.0465
	0.3502	0.2415	0.3638	0.1481
Q3	4.0528	1.9859	3.3503	1.4606
	0.2517	0.1449	0.2768	0.1338
Q4	-2.2666	3.1041	-3.0989	0.1736
	0.662	0.3641	0.9133	0.2168
Q5	1.468	1.972	1.7037	1.4056
	0.4214	0.2582	0.5265	0.3041
Q6	0.3815	2.9825	0.2482	1.9081
	0.3574	0.2375	0.3663	0.1586
Q7	0.212	1.5715	0.3652	1.4044
	0.5028	0.2205	0.6681	0.3278
Q8	-2.0118	-3.706	-0.814	1.0994
	0.8846	0.5009	0.4423	0.2686
Q9	3.6579	2.4182	2.8721	2.3398
	0.2707	0.1555	0.3338	0.1405
Q10	0.2698	2.4268	-0.0044	2.2801
	0.2516	0.2189	0.2392	0.3292
Q11	-0.3522	0.5077	-1.5912	0.7828
	0.2761	0.2452	0.3896	0.1503
β_2			0.2141	0.3469
			0.0905	0.089
β_3			0.1482	0.5949
			0.0859	0.0821

Table 10. Yoplait and Dannon Fixed Effects in Different States

	Without Covariates			With Covariates		
	Other States	State Y	State D	Other States	State Y	State D
Yoplait	4.05	0.51	4.05	3.35	0.10	3.35
	0.25	0.46	0.25	0.28	0.55	0.28
Dannon	3.66	3.66	-0.89	2.87	2.87	-2.60
	0.27	0.27	0.56	0.33	0.33	1.45
Prob. at SS	77.66%	7.86%	14.48%	76.95%	8.05%	15.00%

Table 11. Estimates of Switching Probabilities

	Without Covariates		With Covariates	
	Est	Prob	Est	Prob
pNN	-1.2746	10.565%	-0.7805	18.3373%
	1.2406		1.1149	
pND	-1.2992	10.3238%	-0.7774	18.3928%
	0.4507		0.465	
pNY	0.0877	41.2582%	-0.5433	23.2476%
	0.3208		0.3681	
pDD	2.9665	95.1038%	2.9899	95.2116%
	0.5855		0.4857	
pYY	0.8018	69.0359%	2.0629	88.7245%
	0.4325		0.3791	
pOO	4.2108	98.5382%	3.8243	97.8633%
	0.3376		0.2973	

Table 12. Goodness of Fit across Specifications

	Without Covariates			With Covariates		
	Simple Mixed Logit	Bawa's Model with Mixed Effects	Hidden Markov Model	Simple Mixed Logit	Bawa's Model with Mixed Effects	Hidden Markov Model
Negative Likelihood	5461.7	5449.4	5105.1	5421.7	5411.4	5084
# of Parameters	26	28	33	30	32	37
Choice Occasions	4182	4182	4182	4182	4182	4182

Figure 1. Switching Frequency by Consumer: Eau Claire and Pittsfield

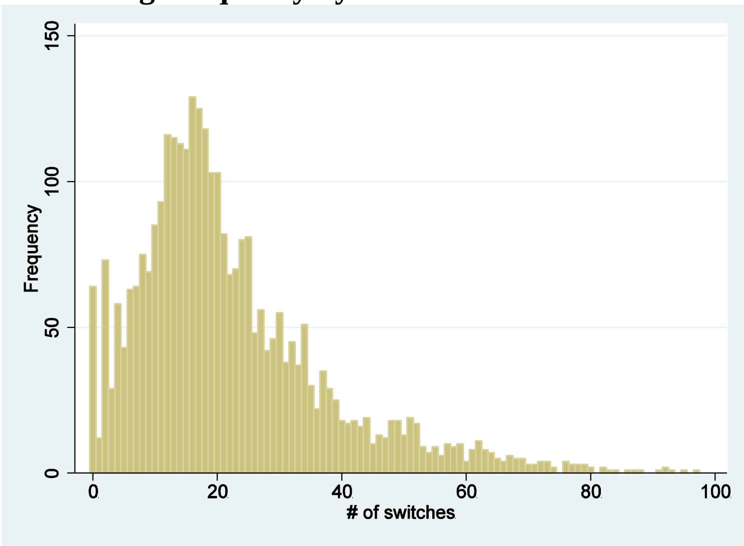
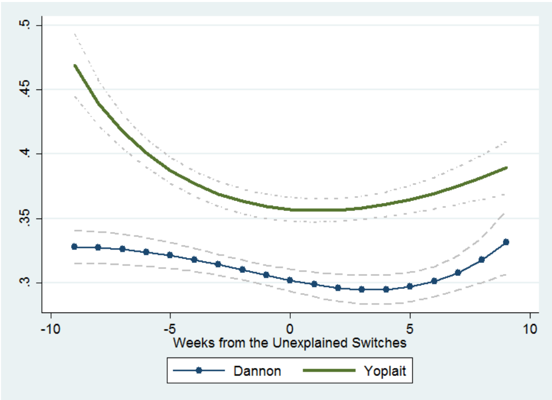
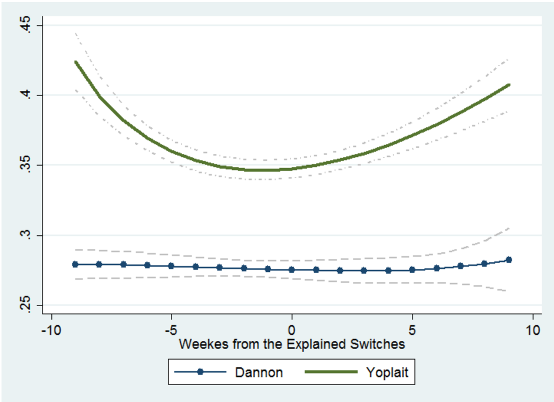


Figure 2 Fitted Choice Probability Curves under Unexplained and Explained Switches

A

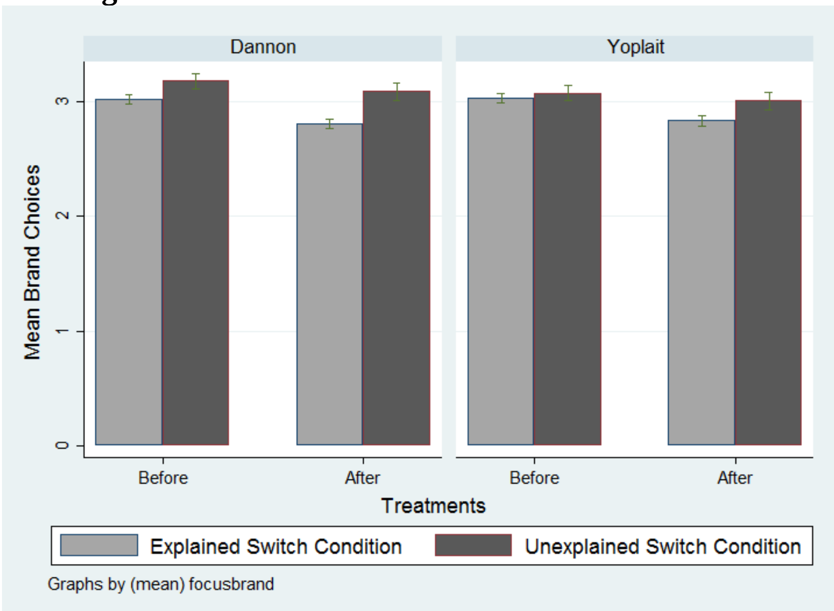


B



Notes: Figure 2A shows the fitted choice probabilities as well as 95% confidence intervals 10 weeks before and after "unexplained switches" from Yoplait or Dannon. Figure 2B shows such probabilities and confidence intervals before and after "explained switches" (by feature ads and price variations). Week 0 in both the figures corresponds to the week after the unexplained switch week. Figure A is associated with higher initial choice probabilities and asymmetric recovery.

Figure 3. Brand Choices around Different Switches



Notes: The above bar graph shows the number of brands chosen 10 weeks before and after unexplained and explained switches. The brands switched to are counted in the "before" category. The variety levels of brand choices in unexplained switch conditions are significantly higher, compared with those in explained switch conditions. The variety levels of brand choices decline significantly in explained switch conditions, but not in unexplained switch conditions.

Appendix

Part A. Estimation Results among Yoplait and Dannon Purchasers

Estimation results for a subsample of consumers who frequently purchase Yoplait and Dannon products appear
Table **13**, Table 14, and Table 15. These consumers have significantly negative (but with much smaller absolute values) price coefficients, compared with the more random original sample. Yoplait and Dannon brands are less preferred during the satiation states--with Dannon exhibiting a deeper satiation effect than Yoplait. In the steady state, consumers are satiated with Dannon products 46.43% of the time, while they are satiated with Yoplait only 33.43% of the time.

Table 13. HMM on a Subsample of Yoplait and Dannon Purchasers

Panel A: Main Coefficients			
	Normal	Satiation	-
	Mean	Mean	Std. Dev
Price	-1.1265	-1.1265	2.8709
	0.3139	0.3139	0.1738
Dannon	-0.2925	-3.4119	2.2664
	0.236	0.311	0.1362
Yoplait	0.9825	-1.4036	1.9213
	0.2779	0.2862	0.1336
Panel B: Transition Matrix			
	Normal	Dannon	Yoplait
Normal	85.82%	7.76%	6.41%
Dannon	3.37%	96.63%	-
Yoplait	3.86%	-	96.14%
Panel C: Steady State			
	Normal	Dannon	Yoplait
Steady State	20.14%	46.43%	33.43%

Table 14. HMM on a Subsample of Yoplait and Dannon Purchasers—Coefficients for Transition Matrix

	Est	Prob
pND	-2.6509	7.76%
	0.467	
pNY	-3.3629	6.41%
	0.4053	
pDD	3.1997	96.63%
	0.41	
pYY	4.0627	96.14%
	0.3539	

Table 15. HMM on a Subsample of Yoplait and Dannon Purchasers: Coefficients for the Normal State

	Mean	Std. Dev		Mean	Std. Dev
A	-1.1265	2.8709	Q7	-3.5384	1.3783
	0.3139	0.1738		0.4966	0.3826
Q1	-3.4451	0.5331	Q8	-4.8359	1.2728
	0.2641	0.2379		0.443	0.2931
Q2	-3.8559	0.6112	Q9	0.9825	1.9213
	0.2829	0.2522		0.2779	0.1336
Q3	-0.2925	2.2664	Q10	-4.3216	1.9718
	0.236	0.1362		0.3797	0.3058
Q4	-3.7072	0.6538	Q11	-9.3184	5.0663
	0.3703	0.3854		1.5718	1.0189
Q5	-4.5177	1.6361	β_2	0.0695	0.766
	0.9134	0.8865		0.1013	0.1288
Q6	-5.481	2.1937	β_3	0.3419	0.5025
	0.7952	0.5733		0.0755	0.0815

Part B. ERIM Data Evidence

The evidence of unexplained switches can also be demonstrated using the ERIM dataset. The ERIM dataset sample for Sioux Falls, South Dakota consists of 461 consumers' purchasing histories (All consumers have more than 20 shopping trips). In all, the yogurt markets in the ERIM dataset contain 21 brands and over 400 sub-brands. Seven major brands[10] in Sioux Falls constitute 97% of the market. We define a composite good as one consisting of all the remaining yogurt brands.

Table A4. Summary Statistics: Sioux Falls

[10] YPLT (YOPLAIT), WW (WEIGHT WATCHER), DN (DANNON), NORDICA, QCH, WBB, CTL.

Brand	Price	Std. Dev.	Min	Max	Scoupon	Mcoupon
YPLT	0.57	0.09	0.25	0.69	48	802
WW	0.45	0.038	0.29	0.52	1	168
DN	0.44	0.071	0.19	0.66	2	278
NORDICA	0.38	0.068	0.23	0.5	392	15
QCH	0.27	0.043	0.15	0.37	0	0
WBB	0.28	0.051	0.14	0.37	0	10
CTL	0.26	0.028	0.12	0.5	1	24

Notes:

1. Price is the average transaction price per six ounces of yogurt.
2. Scoupon represents store coupon and Mcoupon represents manufacturer coupon.

The data support our assumption that consumers often choose a single brand. Looking at consumers' brand choices during each shopping trip in the ERIM datasets, we see that out of 20,881 choice occasions, only 1,620 (7.8%) involve multiple brands.

We calculate the price index using real transaction data. When there is no price information, we approximate the price index using the product in the closest store and the closest week.[11] We factor store coupons in price calculation. Table A4 provides the summary statistics for brand price index with coupon information. From the table, the national brands, including YOPLAIT, WEIGHT WATCHER and DANNON, have relatively higher prices and larger standard deviations than the other brands. We also notice that about 14%, 10%, and 8% of the shopping trips involving, YOPLAIT, WW and DN, respectively involved manufacturer coupons and 7% NORDICA purchases involved store coupons. We do not have information on the coupon usage for the other brands.

Table A5 offers a summary of the switching behavior in the datasets. For example, from the Sioux Falls dataset, 8,785 out of 20,881 total shopping trips involve the purchase of a brand that is not repeated in the next purchase occasion. Yoplait and Weight Watchers have the lowest switching rates, indicating the highest levels of loyalty, while local brands exhibit higher switching rates. To further investigate the source of these switches, we consider changes in relative prices and other marketing mix variables. We define relative price of a brand as the price of that brand divided by the average price of the rest of the brands during the same period. If the brand choice in period t is different from that in period (t + 1), but the relative price of the brand chosen in period t is not increasing and if the relative price of the brand chosen in period (t + 1) is not decreasing, the switch cannot be explained by price. Similarly, if a brand switch between periods t and (t + 1) is not due to a coupon for the target brand in period (t+1) or a coupon for the original brand in period t, the switch cannot be explained by coupons. The sample suggests that even after accounting for relative price changes and other marketing mix variable changes, about 10% of the switches remain unexplained. Although we observe several extremely persistent consumers, the switching behavior is not rare across most consumers. For each consumer, the

[11] The missing price problem has been also discussed in Ackerberg (2001).

average number of shopping trips is approximately 45 and the average number of switches is roughly 19.

Figure A1 shows the histogram plots of switches at the individual level. Given that other product characteristics are relatively stable, this evidence favors a taste variation explanation. Moreover, the national brands Yoplait, Weight Watcher and Dannon, have larger market shares and lower switching rates, supporting the brand loyalty explanation. However, these brands have a higher percentage of unexplained switches than other brands. To further rule out brand switches due to periodic product availability, we also search for unexplained switches only among products that are recorded in the dataset during all the weeks. The results in Table A6 show that there are still significant numbers of unexplained switches.

Figure A1. Switching Frequency: Sioux Falls

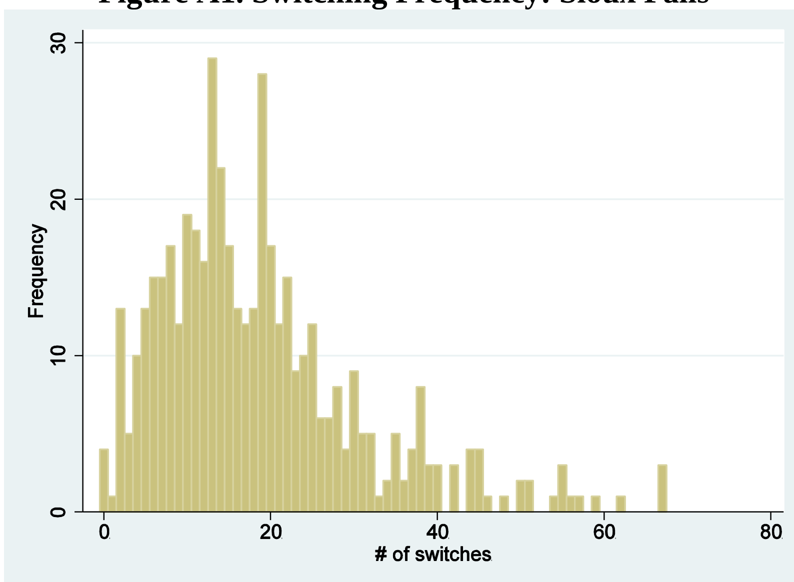


Table A5. Summary Statistics 2: Sioux Falls

Brand	Choice	Total brand switches		Unexplained brand switches		Brand availability	
YPLT	5,710	1,821	31.89%	214	11.75%	170	9.34%
WW	1,565	460	29.39%	73	15.87%	56	12.17%
DN	3,505	1,442	41.14%	161	11.17%	120	8.32%
NORDICA	3,888	1,603	41.23%	102	6.36%	79	4.93%
QCH	1,220	6,55	53.69%	21	3.21%	7	1.07%
WBB	1,517	968	63.81%	76	7.85%	4	-
CTL	2,546	1,201	47.17%	75	6.24%	51	4.25%
Others	930	635	68.28%	49	7.72%	21	3.31%
Total	20,881	8,785	42.07%	771	8.78%	508	5.78%

Notes:

1. "Choice" describes the number of occasions the brand was chosen.
2. A "Brand Switch" is defined as the number of times a consumer switch away from a certain brand.
3. An "unexplained" switch from one brand to another means that both brands are available in the store for two successive periods and that the switch is not due to the following reasons: (a) price discount or coupon from the target brand; (b) price increase by the original brand; and (c) relative price increase of the original brand.
4. The availability adjustment is for sub-categories that exist in all the weeks.