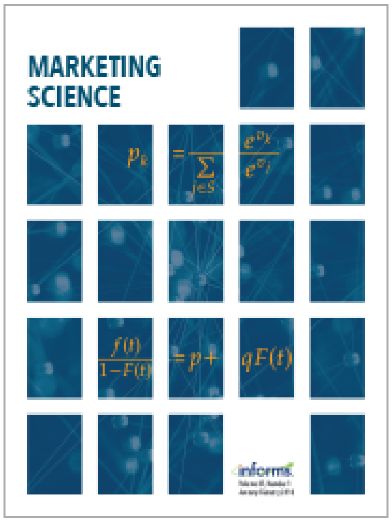

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A Regime-Switching Model of Cyclical Category Buying

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In many categories consumers display cyclical buying: they repeatedly purchase in the category for several periods, followed by several periods of not buying. We believe that the cyclicality is a manifestation of cross-category substitution by the consumer, caused by "variety-seeking" tendencies as well as by the firm's marketing activities in all relevant categories. We propose a Markov regime-switching random coefficient logit model to represent these behaviors as stochastic switching between high and low category purchase tendencies. The main feature of the proposed model is that it divides the stream of purchase decisions of a consumer into distinct regimes with different parameter values that characterize high versus low purchase tendencies. In an empirical application of the model to purchases of yogurt-buying households, we find that as many as 38.3% households display cyclicality between high and low yogurt-purchasing tendencies. Predictions from our proposed model track observed yogurt purchases of households over time closely, and the model also fits better than two benchmark models. Alternating between high and low purchase tendencies may correspond with changing levels of consumer inventory in a substitute category. If one ignores this phenomenon, a correlation between yogurt inventory and the error term in utility arises, leading to biased estimates. Also, we show that cyclicality in buying has a key implication for a firm's price promotion strategies: a price reduction that is offered to a household during its high purchasing tendency period will result in greater increases in sales than one that is offered during its low purchasing period. This opens up a new dimension for enhancing the effectiveness of promotions—customized timing of price reductions.

Key words: random coefficients; logit model; endogeneity; heterogeneity; simulated maximum likelihood; brand choice; scanner data
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1. Introduction

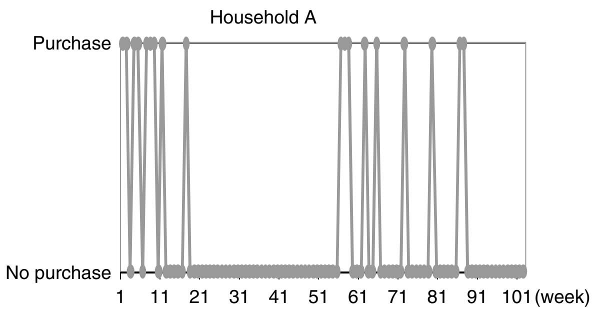
> I think I am seriously addicted to Greek yogurt. For a while, I've been having it every day for breakfast. It's just so good.... Anyway, the point is that I'm a little worried that having the same thing for breakfast every day is not good for me. So I tried having orange-carrot juice and an apple for breakfast. I'm going to try the juice thing or something else for a while though, and maybe later I'll come back to Greek yogurt. It could happen.

The breakfast diary of an anonymous consumer indicates a continuous period of consumption of Greek yogurt, then orange-carrot juice, and then Greek yogurt again. This pattern of behavior is not atypical for frequently purchased, nondurable goods—many readers will recognize similar patterns in their own everyday lives. For some period of time, consumers are strongly inclined to use or consume a certain product repetitively. This "obsession" with the product then ends for various reasons (as we will later discuss) and possibly resumes again after a hiatus.

The consumption behavior of the anonymous consumer quoted above resembles the purchase history of yogurt and other products in IRI household panel data (Bronnenberg et al. 2008).[1] In Figure 1 we show the weekly yogurt purchase behavior of two panelist households over a two-year period. "Purchase" and "No purchase" represent weeks with and without a yogurt purchase, respectively. Household A repeatedly purchases yogurt for the first 17 weeks and then does not purchase yogurt for 38 weeks. Recognizing that yogurt is very perishable, the long period of not purchasing suggests that the household did not *consume* any yogurt for most of this period. This

[1] Note that the data capture panelist households' shopping trips and yogurt purchasing in *all* stores in all retail channels, including grocery, drug, mass merchandise, club, convenience stores, and specialty stores.

Figure 1 Examples of Cyclical Yogurt Purchasing Behavior in Two IRI Panelist Households



no-purchase period is followed by another period of frequent yogurt purchasing, which is followed by another period of not purchasing. Household B shows a similar cyclical purchasing pattern.

How prevalent are such cyclical purchasing patterns? To answer this question, we look in greater detail at the proportion of yogurt-purchasing households that display long periods of nonpurchase and nonconsumption in the IRI data. Because in these data we can only observe purchasing, and not consumption behavior, we consider three product categories that are quite perishable—yogurt, milk, and frankfurters—so that we may be able to infer periods of nonconsumption based on periods of nonpurchasing. We first define the terms "purchase week," "no-purchase week," and "no-consumption period" for the yogurt category (analogous definitions apply to the other two categories). If a household purchases any product in the yogurt category in a certain week, that week is labeled a purchase week and if not, a no-purchase week. A no-consumption period (NCP) is defined as a period of consecutive no-purchase weeks that lasts 10 or more weeks. Our rationale for choosing a 10-week threshold is based on the best by date shown on yogurt containers. We conducted a field survey of this date that revealed that the average best by date is 28 days, or four weeks (standard deviation, 8 days), from the date of purchase (the day we performed the field survey).[2] Even though some households may consume yogurt for a week or two past the best by date, it is very unlikely that a household is consuming inventoried yogurt 10 weeks past the best by date. In other words, our method is likely to understate the occurrence of no-consumption periods.

In IRI's household panels in Eau Claire, WI and Pittsfield, MA, 4,298 panelist households (HHs) purchased yogurt (excluding drinkable yogurt) at least once (i.e., their count of a purchase week is at least one) over a period of 104 weeks in 2003 and 2004. Table 1 shows the distribution of NCPs in the data. Of the 4,298 HHs, 73% show one or more NCPs, and 49% show two or more NCPs. The average length of NCPs in the data is 19.7 weeks. To get insights into households that buy yogurt more frequently, we consider the 1,559 HHs whose count of a purchase week is 20 or more.[3] Of these HHs, 62% show one or more NCPs, and 33% show two or more NCPs. Similar statistics are provided for the milk and frankfurter categories in Table 1. Based on the best by dates that we observed in these categories in our field survey,[4] the NCP is defined as a period of consecutive no-purchase weeks, which lasts 6 weeks or more for milk and 18 weeks or more for frankfurters.

The simple analysis presented in Table 1 reveals that in the three categories, a substantial proportion of households show cyclical category purchase behavior. In each of the three categories, over two-thirds of buying households display at least one episode of several consecutive weeks of no purchases. This episode is long enough that in these perishable categories we can be reasonably certain there is nonconsumption as well. Moreover, this phenomenon is not limited to infrequent category buyers—over half of frequent buyers in the three categories also display at least one such episode.[5]

Our goal is to propose a descriptive model of the kind of cyclical purchasing behavior for which we have provided evidence. We believe that the observed cyclicality is a manifestation of cross-category substitution by the consumer, caused by "variety-seeking"

[2] We visited three grocery stores belonging to three different chains on the East Coast.

[3] The average number of purchase weeks in 4,298 HHs who purchased yogurt during the sample period is about 20.

[4] Our survey revealed that the average best by date is 19 days from date of purchase for milk and 50 days for frankfurters.

[5] A possible alternative explanation of the data in Table 1 is that households were temporarily outside the market area because they were on vacation, for example; hence we do not see yogurt being bought. We find strong evidence against such a vacation theory. If a household was on vacation outside the market area, we should not observe any *visits* to stores in the area. However, we find that on average, a store visit occurred in approximately 80% of the weeks in a NCP for yogurt. We also find that the mean number of store visits per week during consumption periods (2.41) is not significantly different from the mean number during NCPs (2.32).

Table 1 Distribution of NCP in Three Categories

	All category buyers (%)			Frequent category buyers[a] (%)		
	Yogurt $N = 4{,}298$	Milk $N = 4{,}927$	Frankfurters $N = 4{,}460$	Yogurt $N = 1{,}559$	Milk $N = 3{,}127$	Frankfurters $N = 1{,}752$
HHs with NCPs ≥ 1 (%)	73	71	66	62	56	58
HHs with NCPs ≥ 2 (%)	49	54	21	33	32	14

[a]Frequent category buyers are defined as HHs whose count of purchase weeks is at least 20 in yogurt, 40 in milk, and 9 in frankfurters over a 104-week period. These thresholds are the mean counts of purchase weeks in the respective categories.

tendencies as well as by the firm's marketing activities in all relevant categories.[6] A complete, utility-based model of multicategory buying would incorporate these causal phenomena explicitly. However, a significant challenge in applying such a model to data is identifying the complete set of substitute categories and obtaining consumer-level data, including firms' marketing activities, for each category; this is beyond the scope of this paper. Instead, motivated by the same theoretical idea, in the present paper we develop a statistical model of buying in one category. Our statistical model allows for periods of high-versus-low purchasing tendencies in the target category, which leads either to continued purchasing in the category or to not purchasing (which implicitly means switching to a substitute category).

We propose a Markov regime-switching random coefficient logit model to represent switching behaviors between high and low purchase tendencies in a category. The main feature of the proposed model is that it divides the stream of purchase decisions of each consumer into distinct regimes with different parameter values that characterize high and low purchase tendencies. Specifically, we introduce a regime-switching intercept in the consumer's indirect utility function. We interpret the regime-switching intercept as a proxy for the consumer's inventory in categories that are substitutes for the target category. For instance, the consumer in our opening quote tends to consume orange-carrot juice or an apple (substitute categories) during periods when the consumer has a low purchase tendency for yogurt (the target category). The regime-switching intercept approximates the level of substitute inventory, which is unobservable to the researcher but can be inferred from the consumer's purchasing behavior. Previously, similar Markov regime-switching models (or hidden Markov models) have been used to capture changes in consumers' Internet browsing goals (Montgomery et al. 2004) and changes in latent relationship states with the firm (Netzer et al. 2008).

[6] We are grateful to an anonymous associate editor for providing this interpretation.

Consumers are assumed to be heterogeneous in their intensities of high and low purchase tendencies. In addition to category purchase incidence, we also consider consumers' brand choice decisions and the impact of marketing mix variables within the random coefficient logit framework. Because the proposed model nests the typical random coefficient logit model without Markov regime-switching parameters, we can test whether purchase behavior can be better characterized by allowing for switches in category purchase tendencies.

This interpretation of the regime-switching intercept highlights an important methodological concern with models of category purchase incidence. We expect that the target category inventory and substitute category inventory are negatively correlated, and both influence the consumer's purchase decision in the target category. As a consequence, the omission of substitute category inventory may cause an endogeneity problem. This problem is widespread because, to our knowledge, almost all applications of random utility models to category buying ignore substitute category inventory. We investigate the problem of endogeneity of target category inventory empirically and demonstrate how the proposed model handles it.

In addition to including heterogeneity across consumers and parameter dynamics (regime switching), the proposed model also incorporates unmeasured product characteristics (i.e., common shocks) and considers the endogeneity of prices. To handle the endogeneity of prices, we use the control function method (Petrin and Train 2010, Park and Gupta 2009). The resulting Markov regime-switching random coefficient logit model accounts for parameter dynamics, heterogeneity across consumers, endogeneity of prices, and endogeneity of inventory.

We apply the proposed model to yogurt purchases from a sample of households and find that as many as 38.3% of the households display cyclicality in buying, after controlling for the effects of marketing mix variables, state dependence in brand choice, and inventory. Predictions from the proposed model track observed purchases of households closely, and the model also fits better than two benchmark models. We show that if the model ignores the underlying dynamics of switching between high and low purchase tendencies, an endogeneity problem arises.

We also show that cyclicality in buying has a key implication for a firm's price promotion strategies: a temporary price reduction that is offered to a household during its high purchasing tendency period results in greater increases in sales than one that is offered during its low purchasing period. This opens up the opportunity for customized timing of price reductions as a new dimension for enhancing the effectiveness of promotions. We show via simulation that in our sample data, a one-time 30% price reduction on Yoplait with customized timing leads to an 89% increase in the impact of the promotion, relative to a randomly timed promotion. Finally, because the proposed model can be challenging for firms to estimate, we explore the use of simple descriptive statistics of consumers' purchasing behavior (mean and standard deviation of interpurchase times) to classify households into groups based on their cyclicality in category buying. Furthermore, a simple rule of thumb based on past purchasing allows the firm to guess quite successfully whether a household is in the high or low purchase state. These findings reveal an opportunity for firms to improve the efficiency of their promotions without estimating the proposed model.

The remainder of this paper is organized as follows. In §2, we present the model and briefly explain our estimation method (details of the estimation approach are available in the electronic companion to this paper, available as part of the online version found at http://mktsci.pubs.informs.org/). In §3, we describe an empirical application of the model to scanner panel data and discuss our key findings and their managerial implications. Finally, in §4, we summarize the contributions of this article and identify future research issues.

2. Model Formulation and Estimation

2.1. Model Formulation

We assume that on each shopping trip consumers either choose a brand that gives them the highest utility in the category or choose not to purchase in the category. In this paper, we model purchase incidence and brand choice behaviors.[7] On each purchase occasion $t = 1, \ldots, T_h$, the utility for the outside good and the utility of brand $j = 1, \ldots, J$ in store $s = 1, \ldots, S$ for consumer $h = 1, \ldots, H$ is given by the following expression:

$$U^s_{h0t} = \alpha_{h,t} + INV_{ht}\beta_{INV,h} + \varepsilon^s_{h0t}, \quad \text{if no purchase}, \tag{1}$$

$$U^s_{hjt} = \beta_{j,h} + \beta_{s,h} + P^s_{jt}\beta_{P,h} + F^s_{jt}\beta_{F,h} + D^s_{jt}\beta_{D,h} + SD_{hjt}\beta_{SD,h} + \xi^s_{jt} + \varepsilon^s_{hjt}, \quad j = 1, \ldots, J, \tag{2}$$

where INV_{ht} is category inventory carried by household h at the beginning of a purchase occasion (or shopping trip) t, and P^s_{jt}, F^s_{jt}, and D^s_{jt} are the price, feature, and display of brand j in store s at t, respectively.[8] We incorporate state dependence through SD_{hjt}, which is equal to 1 if the last purchased brand is j and 0 otherwise. Individual-specific preferences for brands and stores and responsiveness to price, feature, and display are represented by $\{\beta_{j,h}\}_{j=1,\ldots,J}$, $\{\beta_{s,h}\}_{s=1,\ldots,S}$, $\beta_{P,h}$, $\beta_{F,h}$, and $\beta_{D,h}$, respectively. $\alpha_{h,t}$ represents the utility of the no-purchase option for consumer h at time t. $\beta_{INV,h}$ represents the influence of consumer inventory on category purchase decisions. $\beta_{SD,h}$ captures the individual-specific state dependence effect. A positive coefficient implies positive state dependence, or inertia, whereas a negative coefficient implies variety seeking. Independent and identically distributed (i.i.d.) random shocks with a Type I extreme value distribution are represented by $\{\varepsilon^s_{hjt}\}_{j=0,1,\ldots,J,\, s=1,\ldots,S}$.

The unmeasured product characteristics (UPCs), ξ^s_{jt}, may include, for example, the impact of unobserved promotional activity, coupon availability, shelf space, national advertising, unquantifiable factors, and systematic shocks to demand. We can raise two issues related to ξ^s_{jt}. The first issue is the endogeneity problem. If marketers make their decisions based on the values of ξ^s_{jt}, marketing mix variables would be correlated with ξ^s_{jt}. In particular, empirical research has typically reported a correlation between price and ξ^s_{jt} (or price endogeneity) in disaggregate as well as in aggregate data. Because of this correlation, ξ^s_{jt} is not necessarily mean zero given marketing mix variables, and thus, we cannot treat it as another error component and integrate it out of the demand function. Furthermore, regardless of the correlation with marketing mix variables, ignoring ξ^s_{jt} would force the model to absorb these effects in the i.i.d. random shock and/or the remaining explained part of the utility. As a result, one could get biased estimates of model parameters (Chintagunta et al. 2005, Park and Gupta 2009).

A key feature of our model is consumers' switching between high and low category purchase tendencies.

[7] Purchase quantity is included via an inventory variable that affects the likelihood of buying in the category (i.e., incidence). We do not model the purchase quantity decision. This is reasonable in our empirical application to yogurt, a perishable category in which there is not much quantity variation across occasions (within consumer).

[8] Following Chintagunta et al. (2002), we specify the utility of the outside good as in (1). This specification implies that the preference ordering within the choice set is assumed to be unaffected by the preference orderings in any choice sets that make up the outside good ("weakly separable").

To capture this, we use a Markov regime-switching random coefficients framework. The resulting model divides the purchase stream of each consumer into distinct regimes with different parameter values, and regime-switching dynamics follow a first-order Markov process. We describe a two-regime model and also apply this model to data. An extension to three or more regimes is straightforward. We specify model parameters as follows:

$$\alpha_{h,t} = \bar{\alpha}_0(1 - S_{ht}) + \bar{\alpha}_1 S_{ht} + a_h, \quad a_h \sim \mathrm{N}(0, \sigma_a^2), \tag{3}$$

$$\begin{aligned}\Pr(S_{ht} = 0 \mid S_{ht-1} = 0) &= \frac{\exp(\kappa_{\text{Const}} + \kappa_{HC} HC_h + \kappa_{INV} INV_{ht} + \kappa_{MIX} MIX_{ht})}{1 + \exp(\kappa_{\text{Const}} + \kappa_{HC} HC_h + \kappa_{INV} INV_{ht} + \kappa_{MIX} MIX_{ht})} \\ &= q_{ht},\end{aligned} \tag{4}$$

$$\begin{aligned}\Pr(S_{ht} = 1 \mid S_{ht-1} = 1) &= \frac{\exp(\lambda_{\text{Const}} + \lambda_{HC} HC_h + \lambda_{INV} INV_{ht} + \lambda_{MIX} MIX_{ht})}{1 + \exp(\lambda_{\text{Const}} + \lambda_{HC} HC_h + \lambda_{INV} INV_{ht} + \lambda_{MIX} MIX_{ht})} \\ &= p_{ht},\end{aligned} \tag{5}$$

$$\beta_h = \bar{\beta} + b_h, \quad b_h \sim \mathrm{N}(0, \Sigma), \tag{6}$$

where β_h is a vector of βs, Σ is a covariance matrix of heterogeneity parameters, and HC_h is a household-specific variable that represents household demographics or characterizes household consumption behaviors (we consider household size, average purchase quantity, and the number of category purchases in our empirical application). MIX_{ht} is a household- and time-specific marketing mix variable that influences household's cyclical category buying behavior (we consider price, display, and feature in our empirical application). S_{ht} is an indicator of unobservable discrete states that take the values 0 or 1, where 0 indicates a high category purchase tendency and 1 indicates a low category purchase tendency. Note that the parameter dynamics in $\alpha_{h,t}$ are dominated by S_{ht}, which are individual-specific and evolve idiosyncratically. These determine each consumer's switching behavior between high and low category purchase tendencies. For illustration, let us assume that $\bar{\alpha}_0 < \bar{\alpha}_1$, $S_{ht} = 0$ for $t = 1, \ldots, 10$, and $S_{ht} = 1$ for $t = 11, \ldots, 20$. Then (1), the utility of no purchase, becomes $U_{h0t}^s = \bar{\alpha}_0 + a_h + INV_{h,t}\beta_{INV,h} + \varepsilon_{h0t}^s$ for $t = 1, \ldots, 10$, and $U_{h0t}^s = \bar{\alpha}_1 + a_h + INV_{h,t}\beta_{INV,h} + \varepsilon_{h0t}^s$ for $t = 11, \ldots, 20$. Since $\bar{\alpha}_0 < \bar{\alpha}_1$, the probability of no purchase is lower (i.e., the probability of category purchase is higher) when $t = 1, \ldots, 10$ than when $t = 11, \ldots, 20$. In this manner, we operationalize high and low purchase tendencies. We expect that the level of inventory in substitute categories is low (high) during the high (low) purchase tendency period. Thus, $\bar{\alpha}_0$ and $\bar{\alpha}_1$ can be interpreted as low and high levels of inventory in substitute categories, respectively. Moreover, we expect that $\alpha_{h,t}$ is negatively correlated with INV_{ht}. If the correlation is ignored, an endogeneity problem may arise. This type of endogeneity has been termed "intercept endogeneity" (in contrast with "slope endogeneity"; see Luan and Sudhir 2010). We resolve this issue by specifying a process that governs the correlation. S_{ht} follows the household- and time-specific first-order Markov process specified in (4) and (5). κs and λs link *the likelihood* or *the probability* of regime switches to household- and time-specific characteristics HC_h, INV_{ht}, and MIX_{ht}.

2.2. Model Estimation

There are three issues in the estimation of the proposed model: the first is how to make inferences on the unobservable discrete-state indicator S_{ht}, the second is how to handle heterogeneity related to *a*s and *b*s, and the third is how to handle the unmeasured product characteristics ξ_{jt}^s and the endogeneity of marketing mix variables.[9] To make inferences on the unobservable discrete-state indicator S_{ht}, we first consider the joint density of the observed outcome and the state indicator, and we then integrate the state indicator out of the joint density by summing over all possible values of the state indicator (Hamilton 1989). To handle heterogeneity, we use the simulated maximum likelihood estimator (SMLE). To handle ξ_{jt}^s and the related endogeneity issue, we use the control function method. Details of estimation are provided in Appendix 1 of the electronic companion.

2.3. Benchmark Models

In addition to the proposed model, we estimate two benchmark models that allow us to compare the performance of the proposed model to that of a representative extant approach that accounts for serial dependence in the category purchase decision.

Benchmark 1

$$U_{h0t}^s = \beta_{0,h} + INV_{ht}\beta_{INV,h} + LagInc_{ht}\beta_{\text{LagInc},h} + \varepsilon_{h0t}^s, \quad \text{if no purchase}, \tag{7}$$

$$U_{hjt}^s = \beta_{j,h} + \beta_{s,h} + P_{jt}^s\beta_{P,h} + F_{jt}^s\beta_{F,h} + D_{jt}^s\beta_{D,h} + SD_{hjt}\beta_{SD,h} + \xi_{jt}^s + \varepsilon_{hjt}^s, \quad j = 1, \ldots, J. \tag{8}$$

In this model, a lagged incidence variable $LagInc_{ht}$ is added to the usual random coefficient logit model to capture serial dependence in category purchase incidence (Ailawadi and Neslin 1998). Because our main interest is in the serial dependence in category

[9] Because we observe a household's decision only when it visits stores, t denotes purchase occasion in (1)–(6). However, when we use t in terms that are common to all households, such as ξ_{jt}^s, t denotes calendar time.

purchase incidence, it is reasonable to consider this model as a starting benchmark. $LagInc_{ht}$ is equal to 1 if yogurt was purchased on the last shopping trip and 0 otherwise. Note that state dependence in brand choice is separately considered by the term SD_{hjt}. Also, we consider unmeasured product characteristics and price endogeneity. To estimate this model, we use the control function approach.

As noted previously, the Markov regime-switching coefficient $\alpha_{h,t}$ in the proposed model captures unobservable inventory in substitute categories, which is expected to be negatively correlated with INV_{ht}. If the substitute inventory is an important factor in a consumer's utility but cannot appropriately be explained by $LagInc_{ht}$, then ε^s_{h0t} should absorb the influence of the substitute inventory. Consequently, an endogeneity problem arises in (7) (we refer to this as an "inventory endogeneity problem" hereafter[10]) because of the negative correlation between the regressor INV_{ht} and the random error ε^s_{h0t}. Moreover, we expect that this endogeneity problem will bias the estimate of $\beta_{INV,h}$ negatively. In the next section, we show that the inventory endogeneity problem does arise in our data but is obviated in the proposed model by introducing the Markov regime-switching coefficient $\alpha_{h,t}$.

Benchmark 2

$$U^s_{h0t} = \beta_{0,h} + INV_{ht}\beta_{INV,h} + TE_{ht}\beta_{TE1,h} + TE^2_{ht}\beta_{TE2,h} + (1/TE_{ht})\beta_{TE3,h} + \varepsilon^s_{h0t}, \quad \text{if no purchase,} \tag{9}$$

$$U^s_{hjt} = \beta_{j,h} + \beta_{s,h} + P^s_{jt}\beta_{P,h} + F^s_{jt}\beta_{F,h} + D^s_{jt}\beta_{D,h} + SD_{hjt}\beta_{SD,h} + \xi^s_{jt} + \varepsilon^s_{hjt}, \quad j = 1, \ldots, J. \tag{10}$$

The difference relative to Benchmark 1 is the removal from U^s_{h0t} of $LagInc_{ht}$ and inclusion instead of three functions of TE_{ht}, which is defined as time elapsed since the last purchase. The idea is that $LagInc_{ht}$ might not be flexible enough to model serial dependence in category purchase incidence, and the use of three functions of TE_{ht} offers greater flexibility in this regard. This specification allows for a wide range of hazard shapes and has therefore been used successfully in modeling of interpurchase time (Singh et al. 2006). Also, we can regard these three functions as proxies for substitute inventory that may be related with TE_{ht}. If so, the inventory endogeneity problem will also be remedied.

[10] Note that the inventory endogeneity problem is different from endogeneity because of unobserved product attributes. The former is category, time, and household specific, whereas the latter is time and brand specific.

3. Empirical Analysis

3.1. Data

The data we use are histories of yogurt purchases of IRI BehaviorScan panel HHs in Eau Claire, WI over 104 weeks in 2003 and 2004. The yogurt category is appropriate for the application of the proposed model because yogurt is highly perishable and therefore offers little opportunity to stockpile. Hence, a consumer's switching behavior in category purchasing is mostly due to the consumer's intrinsic consumption preferences, not due to stockpiling.

Among 2,582 panel HHs in this market, 2,206 HHs purchased yogurt (excluding drinkable yogurt) more than once during the sample period. We focus on the three largest grocery stores (IRI key: 233779, 264075, and 653776). Purchases at these three stores amount to 80% of the total yogurt purchases in this area. Of 899 panelist HHs who purchased yogurt only in these three stores, we use data from 519 HHs (58%) who purchased yogurt seven or more times during the 104-week sample period. The use of frequent buyers helps the model identify switching behavior between high and low purchase tendencies. Notably, the selected 519 HHs account for 92% of total yogurt purchases made by the 899 HHs, thus constituting a segment that is of interest to firms in this industry. Hence, we believe our selection rule does not compromise sample representativeness too much.

We include the three largest yogurt brands (Yoplait, Dannon, and Wells) as well as "others" in the analysis. Sales of the three major brands account for 77% of total category sales in our sample. In addition, we include a no-purchase option defined as shopping visits without yogurt purchase. Within each brand, the purchase of any one of the different package sizes was counted as a purchase of the brand.

Prices are defined on a per-pint basis in our analysis. Price, display, and feature at the brand level were computed as market share-weighted averages of UPC-level variables. Descriptive statistics of the purchases and marketing mix variables are shown in Table 2. Approximately 15% of store visits result in purchases of yogurt. Yoplait is the dominant brand in the market, with a 40% market share.

Table 2 **Descriptive Statistics of Yogurt Data**

Brands	No. of purchases	Price ($ per pt) Mean	SD	Feature (percentage of store weeks)	Display (percentage of store weeks)
Yoplait	5,037	1.68	0.14	32	19
Dannon	2,972	1.50	0.12	21	15
Wells	1,723	1.37	0.10	12	10
Others	3,362	1.46	0.15	28	28

Note. Number of households = 519, number of weeks = 104, number of trips = 86,492.

Table 3 Estimation Results of Yogurt Data

	Benchmark 1				Benchmark 2				Proposed model			
	Mean		Heterogeneity		Mean		Heterogeneity		Mean		Heterogeneity	
Variable	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE
INV	**−0.03**	**0.00**	**0.01**	**0.00**	**−0.07**	**0.01**	**0.03**	**0.00**	**0.02**	**0.00**	**0.03**	**0.00**
Store 2	**0.17**	**0.03**	**0.33**	**0.03**	0.00	0.03	**0.21**	**0.03**	**0.25**	**0.04**	**0.36**	**0.03**
Store 3	0.03	0.04	**0.56**	**0.03**	−0.01	0.04	**0.40**	**0.03**	0.02	0.02	**0.37**	**0.05**
Yoplait	**−2.29**	**0.15**	**0.38**	**0.03**	**−2.34**	**0.15**	**0.67**	**0.03**	**−0.82**	**0.16**	**0.63**	**0.03**
Dannon	**−2.76**	**0.14**	**0.37**	**0.03**	**−2.73**	**0.14**	**0.26**	**0.03**	**−1.30**	**0.13**	**0.39**	**0.03**
Wells	**−3.44**	**0.13**	**0.68**	**0.03**	**−3.62**	**0.13**	**1.20**	**0.05**	**−2.27**	**0.13**	**0.97**	**0.04**
Others	**−2.72**	**0.13**	**0.39**	**0.03**	**−2.75**	**0.13**	**0.45**	**0.03**	**−1.37**	**0.13**	**0.86**	**0.04**
Price	**−0.68**	**0.09**	**0.57**	**0.01**	**−0.69**	**0.09**	**0.54**	**0.01**	**−0.83**	**0.09**	**0.51**	**0.01**
Feature	**0.32**	**0.05**	**0.13**	**0.05**	**0.34**	**0.05**	**0.09**	**0.04**	**0.32**	**0.05**	**0.17**	**0.04**
Display	**1.03**	**0.07**	0.09	0.07	**1.04**	**0.07**	**0.12**	**0.07**	**1.04**	**0.07**	**0.16**	**0.07**
SD	**1.27**	**0.02**	**0.78**	**0.02**	**1.05**	**0.02**	**0.32**	**0.02**	**0.95**	**0.02**	**0.71**	**0.03**
LagInc	**−0.30**	**0.03**	**0.17**	**0.03**								
TE/10					0.00	0.08	**0.06**	**0.03**				
$(TE/10)^2$					**0.19**	**0.02**	**0.04**	**0.01**				
1/TE					0.00	0.00	0.00	0.00				
$\bar{\alpha}_1$									**2.10**	**0.03**	**0.12**	**0.02**
Const in q_{ht}									**1.70**	**0.17**		
HC in q_{ht}									**0.92**	**0.08**		
INV in q_{ht}									**−0.08**	**0.04**		
MIX in q_{ht}									0.10	0.09		
Const in p_{ht}									**5.05**	**0.14**		
HC in p_{ht}									**−0.37**	**0.05**		
INV in p_{ht}									**1.28**	**0.34**		
MIX in p_{ht}									0.14	0.10		
LL	−46,275				−46,223				−43,638			
AIC	92,647				92,549				87,388			
BIC	93,096				93,036				87,912			
No. of parameters	48				52				56			

Notes. Estimates in bold are significant at $p = 0.05$. We report and discuss the estimation results for the parameters related to the handling of unmeasured product characteristics in Appendix 2 of the electronic companion.

To control for the endogeneity of price, we use prices at the other stores and quarter dummies as instruments. The price of a brand at a store is highly correlated with prices of the same brand at other stores because competing retailers are likely to be offered the same wholesale prices.[11] However, we do not expect the unmeasured product characteristics, especially those determined at retail (e.g., shelf-space allocation), to be systematically related with wholesale prices. To the extent that this expectation is true, our instrumental variables are valid for controlling for the endogeneity of prices.

3.2. Estimation and Results

Table 3 reports the estimation results of the proposed model and the two benchmark models. As mentioned previously, the benchmark models and the proposed model are estimated with the control function method. For the normalization, we let $\bar{\alpha}_0$, $\beta_{0,h}$, and $\beta_{s=1,h}$ be equal to 0. We specify the covariance matrix of heterogeneity distribution Σ as a diagonal matrix. In (4) and (5), we incorporate the inventory variable INV_{ht} and explanatory variables MIX_{ht} and HC_h into the transition probabilities. In the estimation of the proposed model, we considered (1) household size, (2) average purchase quantity, and (3) the number of yogurt purchases during the sample period as candidates for HC_h in the proposed model. We use the number of yogurt purchases during the sample period because it shows the best result in model fit measures (i.e., log-likelihood (LL), Akaike information criterion (AIC), and Bayesian information criterion (BIC)). Also, we let MIX_{ht} be equal to the average yogurt price at the store where household h visited at time t.

Benchmark 1 is the usual random coefficient logit model with a lagged incidence indicator variable. The mean of the lagged incidence parameter is significant and negative. This tells us that, on average, category purchase on one shopping trip is negatively related to the likelihood of no purchase, or positively related to the likelihood of purchase, on the next trip. This supports the empirical findings of Ailawadi and

[11] The R-square of preliminary regressions of prices on instruments is 0.62 on average (max, 0.85; min, 0.32).

Neslin (1998, p. 393), who attribute a positive effect of lagged incidence on subsequent category purchase to represent "eating bouts, binging, special diets," etc. Both the mean and the heterogeneity parameters of state dependence are positive and significant, and they imply that most households are inertial in their brand choices. As expected, price has a significant negative coefficient, and the effects of feature and display are positive and significant. On average, households' intrinsic brand preferences can be ordered as Yoplait > Dannon = Others > Wells. This preference order is preserved in all three models. The mean parameter of inventory is negative and significant, and this implies that the more inventory a household has, the lower the probability of no purchase. This result is both counterintuitive and counter to what previous research has documented.[12] The same result also occurs in the other benchmark model. We suspect that this is due to the inventory endogeneity problem. Neither benchmark model considers inventory of substitute categories, which is likely negatively correlated with INV_{ht}. As a consequence, ε^{s}_{h0t} contains the influence of omitted substitute category inventory, and a negative correlation between INV_{ht} and ε^{s}_{h0t} biases the estimate of $\beta_{INV,h}$ negatively.

We now consider the effect of including flexible functions of time to capture the serial dependence in purchase incidences by comparing the results of Benchmarks 1 and 2. In Benchmark 2, we use three functions of TE_{ht} instead of $LagInc_{ht}$, and all three fit measures (log-likelihood, AIC, and BIC) improve slightly over Benchmark 1. The mean of estimates for $(TE_{ht}/10)^2$ is significant and positive, but those of $TE_{ht}/10$ and $1/TE_{ht}$ are not significant. Note that the mean parameter of INV_{ht} is still negative and significant. This result tells us that the functions of TE_{ht} do not work as adequate proxies for the substitute category inventory. To summarize, incorporating flexible functions of TE_{ht} enables Benchmark 2 to capture serial dependence in purchase incidence better than Benchmark 1, but this does not solve the problem of inventory endogeneity.

We now discuss the results of the proposed model. The parameters related with individual-level dynamics ($\bar{\alpha}_1$ and σ_α) are significant. These estimates imply that consumers switch between states of high and low purchase tendencies, which are characterized by $\bar{\alpha}_0 = 0$ and $\bar{\alpha}_1 = 2.10$, respectively. Specifically, the average probability of no purchase is 0.61 when $\bar{\alpha}_0 = 0$ and 0.91 when $\bar{\alpha}_1 = 2.10$. Equivalently, the probability of purchasing yogurt on a given visit is 0.39 when a household has a high purchase tendency and is 0.09 when it has a low purchase tendency. Estimates of κ_{HC} and λ_{HC} tell us that HC_h, or the number of yogurt purchases during the sample period, is significantly positively related to the probability of being in a high purchase tendency state and significantly negatively related to the probability of being in a low purchase tendency state. That is, frequent buyer households are more likely to be in a high purchase tendency state, a finding that is intuitive. Estimates of κ_{INV} and λ_{INV} tell us that INV_{ht} is significantly negatively related to the probability of being in a high purchase tendency state and significantly positively related to the probability of being in a low purchase tendency state. This implies that a household is more likely to be in a high purchase tendency state when it has low level of inventory. This finding is also reasonable and consistent with previous empirical literature. Finally, estimates of κ_{MIX} and λ_{MIX} tell us that MIX_{ht}, or the average price, is not significantly related to the transition probabilities.[13]

Using the parameter estimates, we can make inferences on the probability that a certain period t belongs to a specific state. This probability is referred to as the smoothed probability, and we denote it using $\{P(S_{ht} \mid \psi_{hT_h})\}_{t=1}^{T_h}$.[14] By investigating the smoothed probability, we obtain valuable insights into individual-level parameter dynamics, or the households' switching behaviors between high and low purchase tendencies. For the classification of each household's state at t, we assume that household h has high purchase tendency if $P(S_{ht} = 1 \mid \psi_{hT_h})$ is significantly smaller than 0.5 and has low purchase tendency if $P(S_{ht} = 1 \mid \psi_{hT_h})$ is significantly larger than 0.5.[15] Based on these rules, 20.7% of the observations (or 17,943 visits) are classified as a high purchase tendency state, 68.0% (or 58,782 visits) as a low purchase tendency state, and the remaining 11.34% (or 9,767 visits) as an indeterminate state (i.e., $P(S_{ht} = 1 \mid \psi_{hT_h})$ is not different from 0.5). Average durations of high and low purchase tendency states are 56.4 visits (or 35 weeks) and 103.2 visits (or 64 weeks), respectively. Among the 519 households, 199 households (38.3%) show switching behaviors between high and low purchase tendencies during the sample period (we call this group "switching"). Within these households, average durations of high and low purchase tendency states are 31.8 visits (or

[12] For example, Gupta (1988) and Ailawadi and Neslin (1998) report that the effect of household inventory on the probability of no purchase is positive.

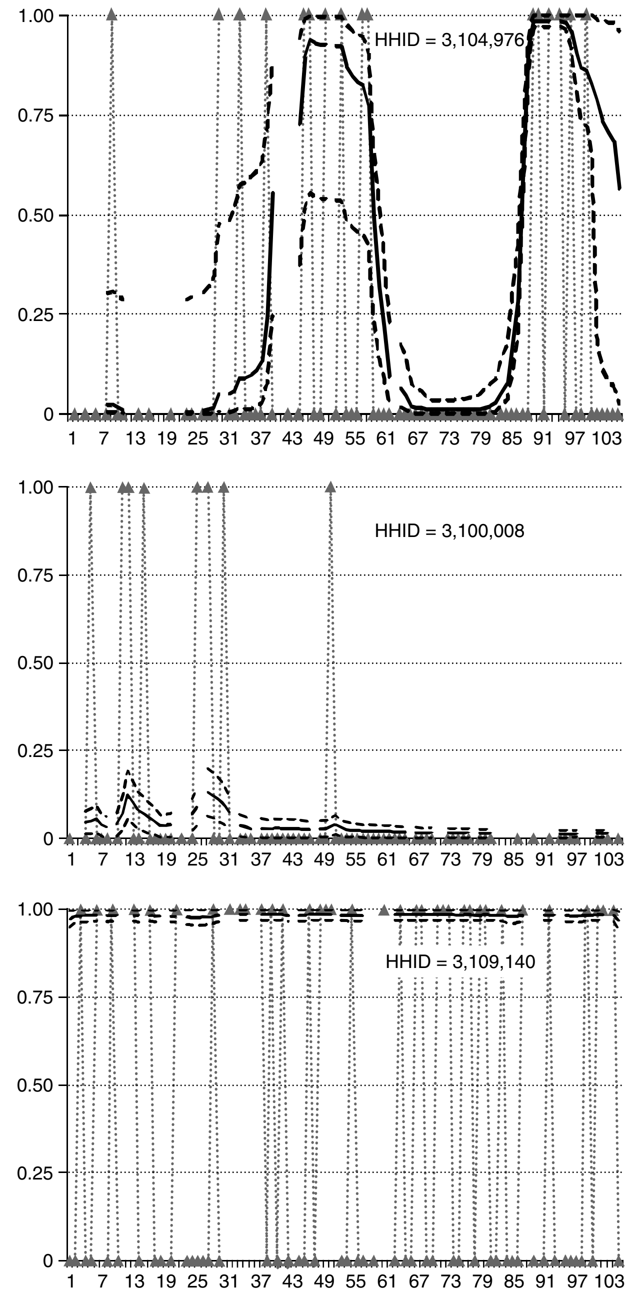
[13] We also specified the average levels of display and feature as MIX_{ht}, but these were not significant either.

[14] We provide more detail about the smoothed probability in Appendix 1 of the electronic companion.

[15] We derive the confidence intervals of smoothed probabilities using the bootstrap method described in Appendix 1 of the electronic companion. We use a 90% confidence interval to determine the significance.

20 weeks) and 62.9 visits (or 39 weeks), respectively. Two hundred twenty-seven households (43.7%) have low purchase tendencies, and 85 households (16.4%) have high purchase tendencies throughout the sample period (we call these groups "low" and "high," respectively). The proposed model's improvement in model fit compared with the static parameter models (i.e., Benchmarks 1 and 2) is mainly attributable to the substantial proportion of households that show switching behaviors. Figure 2 shows $\{P(S_{ht}=0 \mid \psi_{hT_h})\}_{t=1}^{T_h}$ with 90% confidence bands for three representative households. We see that the first household (HHID = 3,104,976) shows switching behaviors between high and low purchase tendencies, the second household (HHID = 3,100,008) has a low purchase tendency, and the last household (HHID = 3,109,140) has a high purchase tendency during the entire sample period.

Figure 2 Examples of Smoothed Probability



Notes. x axis: weeks; y axis: smoothed probability of high category purchase tendency. Triangles indicate observed purchases (=1) and no purchases (=0).

The mean and heterogeneity parameters of inventory (*INV*) are both significant. In particular, most households have positive coefficients, which imply that the larger the inventory before the shopping trip, the higher the utility of no purchase. This result is intuitive and in line with previous empirical studies. Note that the results from the two benchmark models indicate the opposite: the estimated effects of inventory are all significantly negative. The proposed model captures the unobservable substitute inventory using regime-switching variables and thereby overcomes the inventory endogeneity problem.

3.3. Managerial Application: Optimal Timing of Targeted Promotions

The proposed model captures households' switching behaviors between high and low purchase tendencies by introducing a Markov-switching term in the latent utility. What are the managerial implications of such switching behavior of consumers? We answer this question by identifying a unique opportunity for targeted promotions that is implied by the results of our study. In this section, we show via simulation that an understanding of the *dynamic nature* of high and low purchase tendencies is useful in deciding the *optimal customized timing* of a targeted price promotion. Although targeting has been the subject of intensive study in the promotions literature, we believe the question of optimal timing has remained hitherto underexplored.

We focus here only on those households that show switching behavior in their yogurt purchase tendencies (38.3% of the sample households), because identification of this group is a contribution of our model. For this illustration, we assume the role of a product manager of Yoplait who is planning a targeted consumer price promotion—a one-time 30% price-off via a targeted coupon. Our goal is to measure the impact of the temporary price reduction on the choice probability of Yoplait when the *timing* of the offer is *customized to each consumer* based on our knowledge of that household's time-varying category purchase tendencies. This idea is explained in detail next.

Broadly speaking, the question of interest in our two-regime model is whether it is better to offer the price discount when a consumer is in a state of high or low yogurt purchase tendency. We assume

Table 4 Comparison of Price Promotion Strategies

	Proposed model (%)			Benchmark 1 (%)	
	Strategy 1 (Promotion when households have a high purchase tendency)	Strategy 2 (Promotion at 100 random times)		(Promotion at 100 random times)	
Incremental choice probability	77.9	Average	41.2	Average	46.2
		SD	12.3	SD	14.2

that the product manager's objective is to accomplish the greatest increase in unit sales of Yoplait, which is equivalent to maximizing the absolute increase in the choice probability of Yoplait (as indicated by the derivative of the choice probability). For simplification, we do not consider a competitive response to Yoplait's move, although we believe that would be an important extension to consider in future research.

For Yoplait ($j = 1$), the choice probability and derivative of choice probability with respect to price are as follows:

$$\Pr(y^s_{ht} = 1 \mid S_{ht}) = \frac{\exp(V^s_{h1t})}{\exp(\bar{\alpha}_0 S_{ht} + \bar{\alpha}_1(1-S_{ht}) + a_h + INV_{h,t}\beta_{INV,h}) + \sum_{k=1}^{J}\exp(V^s_{hkt})}, \quad (11)$$

$$\text{deriv}^s_{h1t} \mid S_{ht} = \frac{\partial \Pr(y^s_{ht} = 1 \mid S_{ht})}{\partial P^s_{1t}} = \Pr(y^s_{ht} = 1 \mid S_{ht})(1 - \Pr(y^s_{ht} = 1 \mid S_{ht}))\beta_{P,h}, \quad (12)$$

where $V^s_{hjt} = \beta_{j,h} + \beta_{s,h} + P^s_{jt}\beta_{P,h} + F^s_{jt}\beta_{F,h} + D^s_{jt}\beta_{D,h} + SD_{hjt}\beta_{SD,h} + \xi^s_{jt}$. Note that $|(\text{deriv}^s_{h1t} \mid S_{ht} = 0)| > |(\text{deriv}^s_{h1t} \mid S_{ht} = 1)|$ when $\Pr(y^s_{ht} = 1 \mid S_{ht} = 0) < 0.5$.[16] Recalling that $S_{ht} = 0$ indicates a regime of high yogurt purchase tendency, this inequality tells us that the price promotion achieves bigger increases in choice probability during a high purchase tendency period. Intuitively, this result implies that price discounts or other promotional activities are more effective when a consumer is more likely to purchase in the category, conditional on the brand choice probability being less than 0.5. This conclusion is consistent with the commonly observed phenomenon of more promotions being run in high seasons than in low seasons.

To verify this result in our sample yogurt data and to illustrate the importance of understanding the *dynamic nature* of high and low purchase tendencies, we compare the performance of two price promotion strategies using estimation results of the proposed model. Strategy 1 offers a 30% price reduction once in a week when a household has high purchase tendency; Strategy 2 provides a 30% price reduction once in a randomly chosen week (i.e., this is not a customized strategy). Strategy 2 is implemented with 100 random choices of promotion timing. Along with the two strategies based on the results of the proposed model, we perform a similar counterfactual simulation using the results of Benchmark 1. Recall that Benchmark 1 is a random coefficient logit model with a lagged incidence variable and unmeasured product characteristics, but there are no individual-level dynamics in the model. Because lagged incidence was found to have a negative effect on the utility of no purchase, it follows that purchase incidence probability is high immediately after a purchase. Accordingly, we assume that each household is provided with a 30% price reduction once in a randomly chosen week immediately after a category purchase.

Table 4 summarizes the results of the three simulation studies. Strategy 1 attains an incremental choice probability of 77.9% for Yoplait, whereas Strategy 2 attains only 41.2% (on average across the 100 replications). This tells us that a brand manager can increase the impact of a price promotion from 41.2% to 77.9%—a gain of 89%—*merely by optimizing the timing of the price promotion*. In Benchmark 1, the incremental choice probability for Yoplait is 46.2%, which is better than Strategy 2 but considerably worse than Strategy 1.

3.4. Model Implementation Issues

From the perspective of managers, the model we have proposed is quite challenging to estimate. In this section we consider an approach to make the model more managerially useful.[17] To begin with, we examine whether we can predict the classification of households into low, high, and switching groups using descriptive statistics of observed purchase histories as proxies rather than the proposed regime-switching model. For this analysis we divided the original 104-week data into an estimation sample (first 18 months) and holdout sample (last six months). The

[16] This is the case in our empirical analysis and typical brand choice models that include a no-purchase option.

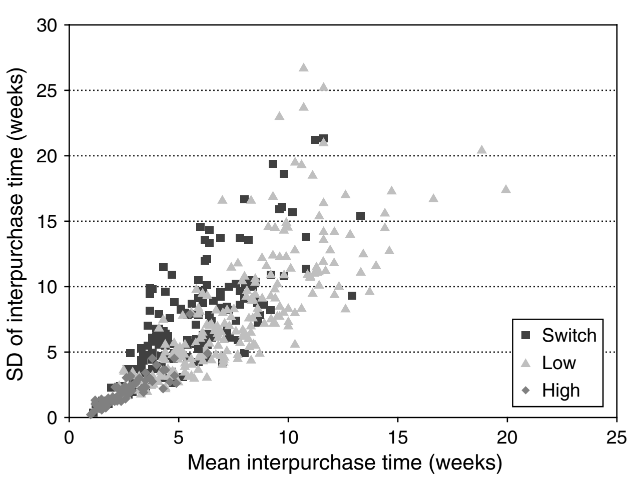
[17] We are grateful to an anonymous associate editor for this suggestion.

proposed model was then estimated on the estimation sample, and households were classified into the three groups using the model estimates. In Figure 3 we show a scatterplot of the three groups of households with respect to the mean and standard deviation of their interpurchase times. This analysis shows that these two variables are likely to be good predictors of households' membership into the three groups. A discriminant model fit to predict households' membership in the three groups using household-level average interpurchase times and household-level standard deviation of interpurchase times as predictors shows good classification ability: the correct classification rate of the model at 63.5% vastly exceeds that because of chance (proportional chance criterion yields 33.4%).

Next, we simulate the effect of a one-off 30% temporary price reduction on Yoplait in the six-month holdout sample data, similar to the exercise described in the previous section. We target 163 households that have been predicted to belong to the switching group by the discriminant model. Note that because of classification error, only 61%, or 99, of these 163 households were identified by the Markov-switching model as switching and the rest were identified as high or low. Strategy 1 is to offer the price reduction to a household when it is in a high purchase tendency state.

To predict the state in the absence of a model, we adopt the following rule of thumb: if a household is observed to purchase yogurt on two consecutive store visits, we assume the household is in a high state. Thus, Strategy 1 is to offer a household the price reduction on the visit immediately after two consecutive yogurt purchase visits. As before, Strategy 2 provides a price reduction once in a randomly chosen week (i.e., this is not a customized strategy). Strategy 2 is implemented with 100 random choices of promotion timing. The incremental choice probability under Strategy 1 is found to be 35.6% whereas under Strategy 2 is found to be 24.4% (averaged across 100 trials). Thus, there is a 46% improvement in performance. Importantly, in this exercise we did not use the estimates from the proposed model, only the conceptual learning that was derived from the model, descriptive statistics of the households' purchasing histories, and a rule of thumb to determine when a household is in a high state.

Figure 3 **Scatterplot of Mean and Standard Deviation of Interpurchase Times by Group**



4. Conclusions and Future Research

We develop a Markov regime-switching random coefficient logit model and apply it to investigate consumers' alternating behavior between high and low category purchase tendencies. We find that purchases in the yogurt category can be better explained by introducing switching levels in the latent utility of no purchase than by a static model, after controlling for the influence of marketing mix variables, inventory, and state dependence. We also find that 38.3% of sample households switched between high and low category purchase tendencies during the 104-week sampling period.

From a methodological point of view, we propose a unique Markov regime-switching random coefficient logit model that incorporates individual-level parameter dynamics. In the empirical application of the proposed model, we show that individual-level dynamics are crucial in explaining individuals' idiosyncratic alternation between high and low category purchase tendencies. Also, we show that alternations between high and low purchase tendencies approximate substitute inventory, and if one ignores these, an inventory endogeneity problem occurs and consequently results in biased estimates. Moreover, to our knowledge, the proposed model is the first time-varying parameter discrete-choice model that considers unmeasured product characteristics and endogeneity of marketing mix variables.

We demonstrate a managerial application of our proposed model to the targeting of customized price promotions. Because 38.3% of sample consumers move between states of high and low category purchase tendencies, their response to a targeted price promotion varies depending on when they receive the promotional offer. We find that offering promotions to consumers when they have a high purchase tendency enhances the effectiveness of the promotion. In the yogurt data, we show that a brand manager can increase the impact of a price promotion by

89% merely by optimizing the timing of price reduction. We believe this finding is noteworthy because it introduces a new dimension to targeted marketing decisions—*timing*. We also show that a firm can implement targeted promotions with customized timing using easily available descriptive statistics of households' purchasing histories.

Several directions exist for further research. Investigating the household's switching behaviors between high and low purchase tendency over multiple categories is an important area for additional research. Dynamics in several categories may be correlated, and this knowledge will be valuable in understanding and predicting consumers' category purchase decisions. Given the nature of our data, our investigation of a consumer's switching behavior remains at a correlational level. In future research, it will be important to explain a consumer's switching behavior in a category purchase at the causal level and identify the underlying mechanisms of such behavior. Also, in the current specification, transition probabilities are explained by household inventory, marketing mix variables, and consumption behavior in the focal category (i.e., yogurt), but not by those in the substitute categories. These omitted variables of substitute categories are likely to be correlated with included variables, and this requires attention in future work.

In this study, the proposed model and two benchmark models are based on the random utility approach. As alternatives to random utility models, marketing researchers have also employed probability models such as Markov chains that may provide an efficient way to model consumers' switching behaviors in multiple categories (Seetharaman 2003).

We believe that the cyclicality is a manifestation of cross-category substitution caused by variety-seeking tendencies and the firm's marketing activities. Alternative theoretical explanations might be consistent with such behavior. In economics, literature on "rational addiction" provides an alternative theory to explain cyclical consumption (Dockner and Feichtinger 1993). In addition to internal factors, external factors (e.g., news, introduction of a new product, price changes, advertising or promotions, and seasonal availability) may also explain consumers' switching behavior between high and low purchase tendency episodes. Disentangling these explanations will provide important insights into consumers' cyclical category buying behaviors.

5. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mktsci.pubs.informs.org/.

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