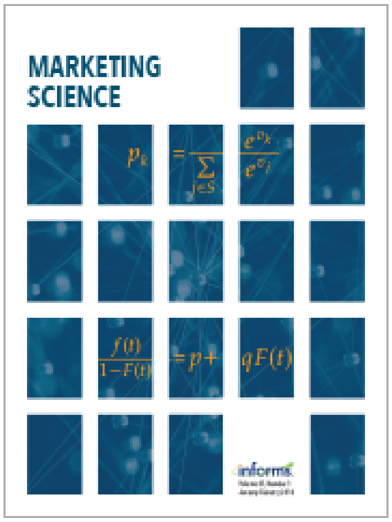

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Promotion Effect on Endogenous Consumption

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Over the years, researchers have found that promotion makes consumers switch brands and purchase earlier or more. However, it is unclear how promotion affects consumption, especially for product categories that are perceived to be versatile and substitutable. In this paper, we propose a dynamic structural model with endogenous consumption under promotion uncertainty to analyze the promotion effect on consumption. This model recognizes consumers as rational decision makers who form promotion expectations and plan their purchase and consumption decisions in light of promotion schedule. Applying the proposed model to packaged tuna and yogurt, we find that endogenous consumption responds to promotion as a result of forward-looking and stockpiling behavior. This is the first empirical paper that recognizes consumption as an endogenous decision variable and proposes a structural model to offer behavioral explanations on whether, how, and why promotion encourages consumption for product categories with flexible consumption.

Key words: promotion; consumption; category expansion; dynamic structural model; forward-looking consumers
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1. Introduction

Does consumption respond to promotion? Many studies have focused on the effects of promotion on brand switching, purchase quantity, and stockpiling and have documented that promotion makes consumers switch brands and purchase earlier or more.[1] The consumers' consumption decision has long been ignored, and it remains unclear how promotion affects consumption (Blattberg et al. 1995). Conventional choice models cannot be used to address this issue because many of these models assume constant consumption rates over time (usually defined as the total purchases over the entire sample periods divided by the number of time periods). While this assumption can be appropriate for some product categories such as detergent and diapers, it might not hold for many other product categories, such as packaged tuna, candy, orange juice, or yogurt. For these categories, promotion can actually stimulate consumption in addition to causing brand switching and stockpiling. Thus, for product categories with a varying consumption rate, it is critical to recognize the responsiveness of consumption to promotion in order to measure the effectiveness of promotion on sales more precisely.

Emerging literature in behavioral and economic theory has provided supporting evidence that consumption for some product categories responds to promotion. Using an experimental approach, Wansink (1996) establishes that significant holding costs pressure consumers to consume more of the product. Wansink and Deshpande (1994) show that when the product is perceived as widely substitutable, consumers will consume more of it in place of its close substitutes. They also show that higher perishability increases consumption rates. Adopting scarcity theory, Folkes et al. (1993) show that consumers curb consumption of products when supply is limited because they perceive smaller quantities as more valuable. Chandon and Wansink (2002) show that stockpiling increases consumption of high-convenience products more than that of low-convenience products. In an analytical study, Assuncao and Meyer (1993) show that consumption is an endogenous decision variable driven by promotion and promotion-induced stockpiling resulting from forward-looking behavior.

In this paper, we develop a forward-looking structural model that recognizes consumers as rational decision makers who plan their future purchases and consumption to coincide with promotion schedules. Optimal consumption decisions are made in light of inventory and promotion in both current and

[1] For disaggregate models, see Guadagni and Little (1983), Gupta (1988), Bucklin and Lattin (1991), Chintagunta (1993), Krishna (1994b), Chiang (1995), Bucklin et al. (1998), Bell et al. (2000), Seetharaman (2003), Neslin et al. (1985), Mela et al. (1998), and Kopalle et al. (1999), among others. For aggregate models, see Mela et al. (1998a, b), Kopalle et al. (1999), Dekimpe et al. (1999), Paap and Franses (2000), Nijs et al. (2001), and Pauwels et al. (2002), van Heerde et al. (2004), Pauwels and Srinivasan (2004), etc.

future periods. This is the first empirical paper that recognizes consumption as an endogenous decision variable and proposes a structural model to offer behavioral explanations on whether, how, and why promotion encourages consumption.[2]

Applying our model to packaged tuna and yogurt data, our analysis sheds new insights on the following issues, which cannot be addressed by previous models with fixed or exogenous consumption rates. First, how does endogenous consumption react to promotion? Managers are interested in the circumstances in which category expansion occurs and the reasons behind these situations (Blattberg et al. 1995). Second, if there is a positive relationship between consumption and promotion, how is this relationship modified by product and promotion-related variables, such as holding costs and promotion uncertainty? This provides important implications for managers to promote the appropriate product category in a more effective way. Third, how to quantify the importance of a consumption increase relative to brand switching and stockpiling? Such an understanding will allow a manager to promote the brand that will cause the least brand switching and purchase displacement but the greatest consumption increase. Fourth, as an application, can the proposed model be adopted to explain the absence of a "postpromotion" dip?

2. Literature

Examining consumers' optimal purchase, stockpiling or consumption behavior under price or promotion uncertainty has attracted increasing attention from theoretical researchers (see Golabi 1985, Meyer and Assuncao 1990, Helsen and Schmittlein 1992, Krishna 1992). Assuncao and Meyer (1993) advance existing theoretical framework by allowing consumer's rate of consumption to be a decision variable. They conclude that consumption should rationally increase with the size of existing inventories. Ho et al. (1998) show that the average optimal consumption rate increases with price fluctuation. Bell et al. (2002) show that flexible consumption causes more intense price competition. Although these papers provide important theoretical justifications for forward-looking purchase behavior and promotion effect on consumption, their normative conclusions need to be empirically tested.

There are some recent empirical papers addressing the promotion effect on consumer stockpiling behavior under price or promotion uncertainty. Erdem and Keane (1996) and Gonul and Srinivasan (1996) establish that consumers are forward looking. Erdem et al. (2003) explicitly model consumers' expectations about future prices with an exogenous consumption rate. In their model, consumers form future price expectations and decide when, what, and how much to buy.[3] Sun et al. (2003) demonstrate that ignoring forward looking behavior leads to an overestimation of promotion elasticity.[4] However, the frameworks developed in these papers cannot be adopted to study promotion effect on consumption because they assume constant or exogenous consumption, which is independent of promotion.[5]

The only published empirical paper that studies the promotion effect on consumption is Ailawadi and Neslin (1998), which adopts nested logit model and establishes a positive statistical relationship between consumption and inventory. Compared with their reduced form approach, our proposed dynamic structural model with endogenous consumption decision under promotion uncertainty offers several advantages to study the promotion effect on consumption: (1) It treats both promotion and inventory as state

[2] Although the importance of empirically testing how promotion encourages endogenous consumption has long been recognized (e.g., Neslin and Stone 1996), it remains a challenging task in terms of both modeling and computation. Endogenizing consumption requires that the optimization problem be solved for optimal consumption. In a dynamic model, optimal consumption needs to be solved over multiple periods of time. With multiple brands and quantity decisions, the curse of dimensionality of endogenous consumption in dynamic programming estimations becomes computationally very intensive.

[3] Erdem et al. (2003) develop several novel components in their model, such as household's usage rate, fixed cost associated with purchase, inventory cost, and comprehensive price process. These components allow them to provide detailed behavioral explanations on consumer brand and quantity choice dynamics under price uncertainty. Consumption is assumed to be exogenously given. Different from their paper, the focus of our study is to investigate how endogenous consumption responds to promotion, an issue that has never been examined before. To focus on endogenous consumption, we do not include all the novel components from their paper but instead follow Gonul and Srinivasan (1996) and Sun et al. (2003) in modeling inventory and price process. This significantly reduces the computational burden and offers us the flexibility to endogenize consumption.

[4] Sun et al. (2003) study whether brand switching elasticities are overestimated if consumers' stockpiling behavior is ignored. They assume consumption rate is exogenous and constant. On the contrary, this paper establishes that consumers make strategic consumption decisions in response to promotion.

[5] There is a recent working paper by Hendel and Nevo (2002), who propose a dynamic model of purchase and consumption decisions. They assume that consumers solve a dynamic quantity choice problem and then separately solve a static brand choice problem, which breaks down when there is consumer heterogeneity. In addition, they assume that the price process of different brands is described by a single category price index, which fails when different brands have different price processes and cannot be used to conduct policy simulations in which one brand alters its pricing. The focus of their paper is to show that price elasticity can be significantly overestimated if we ignore dynamics. On the contrary, in our model, consumers solve a joint quantity and choice problem. We incorporate unobserved heterogeneity and allow price process to be different across brands. Most importantly, our focus is on endogenous consumption rather than price elasticity.

variables driving a sequence of endogenous purchase and consumption decisions; (2) it provides behavioral explanations on not only whether consumption varies with respect to promotion, but also why (e.g., promotion-induced stockpiling) and how (e.g., the promotion-consumption relationship increases with holding cost and decreases with promotion uncertainty) it occurs; and (3) it provides more reliable simulation results because it is not subject to the "Lucas critique" that parameters estimated using reduced form models are not robust to policy change.

3. Dynamic Model with Endogenous Consumption under Promotion Uncertainty

3.1. Model Setup

3.1.1. Consumption Utility. Suppose consumers $i = 1, \ldots, I$ visit stores on a periodic (e.g., weekly) basis for $t = 1, \ldots, T$. In the store, there are $j = 1, \ldots, J$ competing brand choices in addition to the default nonpurchase choice $j = 0$. Each consumer observes prices and promotions for all the competing brands in a product category of interest.[6] At each time period, consumer i decides which brand j to purchase and how much to consume. For each brand j, the consumer can choose among a discrete set of available quantities q. We assume that household i has the following per period utility function at time t:[7]

$$U_t = \sum_{j=1}^{J} \phi_j (c_{jt} - \gamma c_{jt}^2) + \alpha Z_t, \tag{1}$$

where c_{jt} is the quantity of consumption of the focal category for brand j, and Z_t is the quantity of all other goods consumed in week t. The parameter α measures the benefit from consuming the composite of other goods. The parameter ϕ_j represents the unit consumption benefit associated with brand j for consumer i. The parameter γ represents the degree of risk aversion.

3.1.2. Budget Condition, Purchase, and Expenses. At time t, consumer i has an exogenous budget y_t allocated for all purchases and inventory costs. Let P_{jt} denote the price associated with purchasing brand j. Because the unit of the composite goods is scalable, we normalize the price of the composite good to one. Let q_{jt} denote the purchase quantity and I_{jt} denote the inventory of brand j for consumer i at time t. We assume that the goods are durable and goods not consumed can be stored at a unit holding cost of θ. Then we have the following budget constraint:[8]

$$y_t = \sum_{j,q} d_{jqt}(P_{jt} * q_{jt}) + Z_t + \theta \sum_{j=1}^{J} I_{jt}, \tag{2}$$

where a dummy variable $d_{jqt} = 1$ denotes a purchase of brand j and quantity q.[9]

$$d_{jqt} = \begin{cases} 1, & \text{if the consumer chooses brand } j \\ & \quad \text{and quantity } q \text{ at time } t, \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

The inventory of brand j evolves according to the following relationship:

$$I_{jt} = I_{j(t-1)} + q_{j(t-1)} - c_{j(t-1)}. \tag{4}$$

Substituting the budget condition (2) into the utility function (1), we get the following expression for the per-period utility function:

$$U_t = \sum_{j=1}^{J} \phi_j (c_{jt} - \gamma c_{jt}^2) + \alpha \left(y_t - \sum_{j,q} d_{jqt} P_{jt} q_{jt} - \theta \sum_{j=1}^{J} I_{jt} \right). \tag{5}$$

To simplify the notations, we define $I_t = \sum_{j=1}^{J} I_{jt}$ as the category inventory at time t. Moreover, because y_t enters the utility function for different brand-quantity decisions in the same way, it will not affect brand-quantity decisions. Dropping this common term across brand-quantity choices, the per-period utility function can be written as

$$U_t = \sum_{j=1}^{J} \phi_j (c_{jt} - \gamma c_{jt}^2) - \alpha \sum_{j,q} d_{jqt} P_{jt} q_{jt} - h I_t, \tag{6}$$

where $h = \alpha\theta$. In Equation (6), parameter α measures consumer sensitivity to total price (or expenditure). The parameter h measures the unit holding cost, which is assumed to be linear with respect to inventory and constant over the planning horizon.

[6] In the following discussion, we do not explicitly differentiate price and promotion. We refer change of price as price promotion. Because both price and promotion are state variables if treated separately, this simplification significantly reduces the computational burden without affecting the main result and is consistent with Erdem et al. (2003).

[7] For the ease of exposition, we ignore the subscript i in all variables. Later, we add heterogeneity and subscript i to relevant variables starting in §3.2.

[8] We include inventory costs in the budget constraint. This is equivalent to including inventory costs directly in the utility function. See Erdem et al. (2003) and Sun et al. (2003) for a similar treatment of inventory cost.

[9] Note we treat brand-quantity combination as a discrete choice. This is consistent with recent papers in economics and marketing that develop dynamic structural models to study the effects of promotion on stockpiling.

3.1.3. Dynamic Programming. We model the consumer's purchase and consumption decisions as a dynamic optimization problem under promotion uncertainty. The consumer's task is to decide which brand to buy, how much to buy and how much to consume given current inventory and promotion so as to maximize the sum of discounted expected future utility U_t over the infinite horizon.

$$\underset{c_{jt},\, d_{jqt}}{\text{Max}}\, E_t\left\{\sum_{\tau=t}^{\infty}\delta^{\tau-t}(U_\tau+\epsilon_\tau)\right\}. \quad (7)$$

The variable δ is the discount factor to reflect the fact that consuming now is preferred to consuming later (for example, the interest rate). The operator $E_t[\cdot]$ denotes the conditional expectation operator given the consumer's information at time t. The variable ϵ_t is a random shock to utility that affects consumer i's decision. We assume that $\epsilon_t = \sum_{j,q} d_{jqt}\epsilon_{jqt}$ where ϵ_{jqt} has an i.i.d. extreme value distribution to obtain multinomial logit choice probabilities.

Given the one-period utility function, we have the following Bellman equation for the optimal decisions:

$$V(F_t) = \max_{c_{jt},\, d_{jqt}} \sum_{j=1}^{J}\phi_j(c_{jt}-\gamma c_{jt}^2) - \alpha\sum_{j,q} d_{jqt}P_{jt}q_{jt} - hI_t + \epsilon_t + \delta E[V(F_{t+1}) \mid F_t], \quad (8)$$

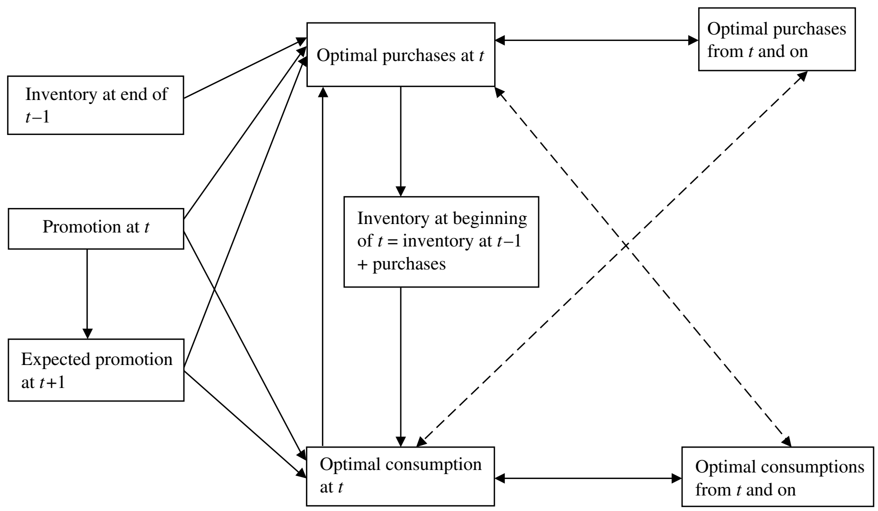
where F_t denotes the information set available to consumer i at time t. The consumer knows the inventory level at the end of last period and observes current prices. We let S_t denote the state variables, which include the exogenous state variables such as current prices and endogenous state variables such as current inventories. The decision variables are sequences of brand-quantity choices d_{jqt} and consumption c_{jt}. Following Equation (8), the optimal consumption maximizes the value function given the optimal brand-quantity decision, d^*_{jqt}:

$$c^*_{jt} = \arg\max_{c_{jt}}\left\{V(F_t) = \sum_{j=1}^{J}\phi_j(c_{jt}-\gamma c_{jt}^2) - \alpha\sum_{j,q} d^*_{jqt}P_{jt}q_{jt} - hI_t + \epsilon_t + \delta E[V(F_{t+1}) \mid F_t]\right\}, \quad (9)$$

where c^*_{jt} denotes the optimal current consumption, which depends on the exogenous state variables P_{jt}; endogenous state variables I_{jt}; the brand-quantity decision d^*_{jqt}; parameters such as δ, h, γ; and parameters that describe the price process of different brands. As shown in Figure 1, current optimal consumption depends on the inventories through the dependence of $V(F_{t+1})$ on the inventories. Current optimal consumption is also related to price for the following reason: It will affect expectations of future prices, which affects the next period value function $\delta E[V(F_{t+1}) \mid F_t]$ and thus changes the relative trade-offs between current and future consumption. The indirect effect about future value function will also affect the level of current consumption. Moreover, optimal consumption depends on the optimal brand-quantity decision d^*_{jqt} which is also directly affected by inventory level and prices.

The time line of the decision process is as follows: At the beginning of time t, the consumer is aware of the leftovers from last period. She also observes promotion available at the store and forms expectations for future promotion. Given current inventory, current promotion, and expected future promotion, she makes a purchase decision at the store. Returning home, the consumer decides how much to consume based on her available inventory (the sum of leftovers from last week and optimal new purchases), current promotion and future promotion expectation.

Figure 1 A Graphical Description of the Relationship Among Purchase, Consumption, and State Variables



The consumer's decisions are time consistent in that she knows what she will do in the future periods, and her decision in the future will be subgame perfect (i.e., the consumer's decision in future periods is optimal conditional on the information she has in the future). Thus, both current and future purchase and consumption decisions are interdependent and depend on current inventory and promotion.

3.1.4. Store Visits. We observe from the data that consumers sometimes do not visit the store. If the consumer visits the store, her behavior is described by the above model. If she does not visit the store, she chooses only the amount of consumption and does so to maximize the current consumption utility, minus inventory costs, plus discounted future expected utilities. It is important to model store visits because random store visits create extra precautionary incentive to hold inventories. Consumption also varies with duration between visits.

We use a binomial distribution to model store visit behavior.[10] In each period, there is a probability ρ that she will visit the store next period. Let the value function in periods of store visits be $V(F_t)$ and the value function of no store visit be $W(F_t)$. The Bellman equations for store visit and no store visit are given below:

$$V(F_t) = \max_{c_{jt},\, d_{jqt}} \sum_{j=1}^{J} \phi_j (c_{jt} - \gamma c_{jt}^2) - \alpha \sum_{j,\,q} d_{jqt} P_{jt} q_{jt} - hI_t + \epsilon_t + \delta E[\rho V(F_{t+1}) + (1-\rho) W(F_{t+1}) \mid F_t], \tag{10}$$

$$W(F_t) = \max_{c_{jt}} \sum_{j=1}^{J} \phi_j (c_{jt} - \gamma c_{jt}^2) - hI_t + \delta E[\rho V(F_{t+1}) + (1-\rho) W(F_{t+1}) \mid F_t]. \tag{11}$$

We approximate the value of ρ using the sample frequency of store visits.

3.1.5. Expectation of Price Promotion. We assume that the log price of brand j follows a first-order Markov process. We also take into account competitive reaction and the time trend of price. Thus,

$$\ln P_{jt} = \lambda_{1j} + \lambda_2 \ln P_{j(t-1)} + \lambda_3 \frac{1}{J-1} \sum_{l \neq j} \ln P_{l(t-1)} + \lambda_4 t + \eta_{jt}, \tag{12}$$

where λs are coefficients. The variable η_{jt} is the random shock of brand j at time t. We assume the random shocks in prices of all J brands, η_t, follow a multivariate normal distribution:

$$\eta_t \sim N(0, \Sigma_\eta). \tag{13}$$

[10] Hendel and Nevo (2003) also use binomial distribution to model store visits.

Competitor reaction is captured by entering the mean price of all competing brands in the price process. The diagonal elements in Σ_η denote the corresponding variance of η_j, and the off diagonal elements denote the covariance between prices of different brands. Allowing random shocks to be correlated can further capture the co-movement of prices of the competing brands. The price process parameters are estimated using the price data prior to the estimation of the model. The price process parameters are then treated as known in the model estimation when we solve the consumer's dynamic optimization problem.

3.2. Heterogeneity and Estimation

In this section we introduce heterogeneity to the coefficients in Equations (10) and (11). Let $\omega_i = (\phi_{ij}, \gamma_i, \alpha_i, h_i)$ be the multivariate normal distribution that generates these coefficients:

$$\omega_i \sim N(\bar{\omega}, \Sigma_\omega), \tag{14}$$

where $\bar{\omega} = (\bar{\phi}_j, \bar{\gamma}, \bar{\alpha}, \bar{h})$ is the mean of ω_i, and Σ_ω is a diagonal variance/covariance matrix of dimension $J+3$ with the diagonal elements denoting the corresponding variance of each parameter.

Formally, for a given value of the parameter, the log-likelihood function of the sequence of choices of all the households is

$$\sum_{i=1}^{I} \log(\Pr(D_{iT}^h \mid S_{iT}^h)) = \sum_{i=1}^{I} \log\Big(\int \Pi_{t=1}^{T} \Pr(D_{it} \mid S_t, I_{t-1}(I_1, D_{i(t-1)}^h), \omega_i)\, dF(\omega_i)\, dF(I_1) \Big), \tag{15}$$

where I_1 denotes the initial inventory and $D_{it}^h = (D_{i1}, \ldots, D_{it})$ denotes the history of $D_{i\tau}$ for τ from 1 up to t. Similarly, $S_{it}^h = (S_{i1}, \ldots, S_{it})$ denotes the corresponding history of exogenous state variables, purchase prices and store visits from 1 up to t. Let $\mathcal{T}_i$ denote the set of time periods in which consumer i visits the store. Given the extreme value distribution of the error term, the probability of observing consumer i making decision D_{it} at time $t \in \mathcal{T}_i$ is

$$\Pr(D_{it} \mid S_{it}, I_{it-1}, \omega_i) = \frac{A_{it}}{B_{it}}, \tag{16}$$

where

$$A_{it} = \sum_{j,\,q} \exp(V_{ijqt}) * d_{ijqt}, \tag{17}$$

$$B_{it} = \sum_{j,\,q} \exp(V_{ijqt}), \tag{18}$$

and d_{ijqt} denotes the observed brand and quantity choice at time t for consumer i, V_{ijqt} is the value function for choice j, q for consumer i at time t and is given by

$$V_{ijqt} = \max_{c_{ijt},\, d_{ijqt}} \sum_{j=1}^{J} \phi_{ij}(c_{ijt} - \gamma_i c_{ijt}^2) - \alpha_i P_{jt} q_{ijt} - h_i I_{it} + \delta E[\rho V_i(F_{t+1}) + (1-\rho) W_i(F_{t+1}) \mid F_t]. \quad (19)$$

In summary, the state variables are price, inventory, and store visits. Among these, inventory is an endogenous state variable, while price and store visits are exogenous state variables. Because of the complexity of the dynamic programming problem, we adopt simulated maximum likelihood techniques employing Monte Carlo methods (Keane 1993) in addition to the interpolation method (Keane and Wolpin 1994) to estimate the model, which significantly reduces the computational burden and makes the endogenization of consumption possible.[11]

4. Empirical Application

4.1. Data Description

We use "lite" tuna and yogurt data collected by the A. C. Nielsen Company and focus on purchases of leading brands, which comprise more than 93% and 74% of the market share for tuna and yogurt, respectively. For both categories, the calibration samples consist of 6,200 observations from 50 randomly selected households during 124 weeks from 1986 to 1988 in Sioux Falls, South Dakota. These households made 839 purchases of tuna and 1,440 purchases of yogurt during the observation period. Table 1 reports the descriptive statistics. Consumers usually buy more than their average consumption. For example, the average purchases per incidence are 2.77 and 2.57 cans of 6.5-oz. for StarKist and CKN. Consumers' average consumption per week for StarKist and CKN is 0.48 and 0.31 cans of 6.5-oz. tuna, respectively. We reserve 980 observations from 49 households over the course of 20 weeks who made 145 purchases of tuna and 248 yogurt in Springfield, MO for cross sample validation.

[11] We point out three issues in the empirical application. First, because the state variable P_{jt} is continuous, it is impossible to solve exactly for V_{ijqt}, W_{ijqt} at every state point. We consider 12 inventories and 10 prices (drawn i.i.d. from a uniform distribution) for the two brands in analysis. Thus, we calculate the value function on $G = 14,400$ grid points. Second, although we specify the DP problem over an infinite horizon, we find convergence of the backward induction process when $T = 248$, which is twice the number of sample periods. Third, we start with an initial inventory of zero and solve the dynamic programming problem for the whole time span for $M = 10$ times to simulate the initial inventory distribution for a consumer.

Table 1 Descriptive Statistics

Brands	Market share	Average price per ounce (cents)	Average purchase quantity[a]
Tuna category			
StarKist	67.73	0.111	2.77
CKN	32.27	0.104	2.57
Yogurt category			
Nordica	34.61	0.0642	1.99
Yoplait	28.16	0.0983	2.18
Private label	19.92	0.0450	1.82
Dannon	17.31	0.0871	1.93

[a]The purchase quantities are number of units. The unit refers to 6.5 oz. for tuna and 6 oz. for yogurt.

4.2. Estimation and Comparison

We compare our dynamic structural model with four baseline models.[12] The first baseline model is a nested logit model with fixed consumption. The second model is similar to Ailawadi and Neslin (1998), which is a nested logit model with a varying but exogenously given consumption rate. Model 3 is a static version of our proposed model. Model 4 is a forward-looking model with constant consumption. It is similar to Sun et al. (2003) and Erdem et al. (2003) because it assumes that the consumption rate is not endogenously driven by inventory and promotion. Model 5 is our proposed structural model with endogenous consumption under promotion uncertainty. As indicated in Table 2a, for tuna category, the comparisons of log-likelihood values, AIC and BIC show that model fit improves from Model 1 to Model 5 with Model 5 being the best-fitting model. Model 4 fits the data worse than Model 5, which indicates that it is important to treat consumption as a decision variable that can be endogenously driven by promotion and inventory. Model 3 underperforms Model 5, indicating that consumer are indeed forward-looking and strategically plan their purchase and consumption decisions. Models 3 and 4 are our proposed models without dynamics and endogenous consumption, respectively. The comparison of these two models with our proposed model reveals that both components are important in improving data fitting. The model comparison results from the holdout sample support our hypothesis that consumers not only strategically plan their future purchases, but also their future consumption in light of inventory and promotion.

[12] The estimation and simulation results are similar for tuna and yogurt categories. To save space, we report model comparison and coefficient estimation results only for tuna category. The policy simulation results are reported for both categories. We point out the major difference in simulation results between the two categories. Interested readers can obtain the estimation results of yogurt category from the author.

Table 2a Model Comparison

Tuna category					
	Reduced form models		Structural models		
Model fit statistics	Model 1	Model 2	Model 3	Model 4	Model 5
Calibration sample[a]					
Log-likelihood	6,659.0	6,627.1	6,620.2	6,609.2	6,575.8
AIC	6,687.0	6,656.1	6,630.5	6,619.2	6,585.8
BIC	6,781.3	6,753.7	6,663.9	6,652.9	6,619.5
Holdout sample					
Log-likelihood	1,035.2	1,004.2	1,000.1	992.2	957.3
AIC	1,063.2	1,033.2	1,010.1	1,002.2	967.3
BIC	1,131.6	1,104.1	1,034.6	1,026.7	991.9

[a]Calibration sample: Number of households = 50; Number of weeks = 124; Number of observations = 6,200. Holdout sample: Number of households = 49; Number of weeks = 20; Number of observations = 980.

Table 2b Sample and Simulated Purchase Incidence, Choice, and Quantity

Tuna category				
	Sample	Model 3	Model 4	Model 5
Percentage distribution of duration between purchases (weeks)				
1	5.31	5.24	5.26	5.28
2	4.87	4.90	4.89	4.86
3	3.82	3.80	3.80	3.79
4	4.57	4.63	4.62	4.6
5	8.92	9.01	8.99	8.97
6	13.47	13.39	13.41	13.51
7	20.35	20.04	20.18	20.3
8	18.22	18.15	18.16	18.18
9	12.56	12.50	12.49	12.53
10+	7.91	8.34	8.20	7.98
Choice probabilities				
No purchase	86.11	84.74	84.99	85.79
StarKist	9.52	11.26	11.13	10.01
CKN	4.37	4.00	3.88	4.20
Average purchase quantity				
StarKist	2.77	2.80	2.79	2.75
CKN	2.57	2.55	2.56	2.61

The advantage of the structural model is that it explains the behavior process rather than "fits" the data, as does a reduced form model (a very reduced form model can fit better than a structural model without explaining consumer decision process). We now demonstrate how the proposed structural model "approximates" the data. In Table 2b, we compare the simulated frequency distribution of durations between visits, choice probabilities, and average purchase quantity with those from the sample. The fit of our proposed model is remarkably good on all these dimensions, indicating that the proposed model approximates the data very well.

Table 3a reports the maximum likelihood estimates of parameters in the price process. Most of the coefficients are significantly estimated except that of the time trend and covariance. The coefficient of the average of competitors' price is positive and significant implying StarKist increases its price if the average last period price of competitors is higher. The covariance between StarKist and CKN is insignificant, indicating that there is no clear tendency for the price shocks to move in the same direction. This finding is consistent with Erdem et al. (2003).

Table 3a Estimates of the Price Process

Tuna category	
Parameter	Estimate
Brand constant λ_1:	
StarKist	−0.551 (0.16)
CKN	−0.265 (0.08)
Lagged price λ_2:	−0.134 (0.06)
Average prices λ_3:	0.063 (0.021)
Time trend λ_4:	0.0008 (0.0007)
Variance covariance matrix Σ_η:	
$\Sigma_{\eta_{11}}$:	0.074 (0.023)
$\Sigma_{\eta_{12}}$:	−0.011 (0.007)
$\Sigma_{\eta_{22}}$:	0.087 (0.029)

In Table 3b, we report the estimation results of the five competing models with mean parameter estimates reported in the first line and the standard deviation estimates across households reported in the second line.[13] We follow the convention and fix the weekly discount factor at 0.995. Because Model 5 is the best fitting model, we focus on the estimation results of Model 5 in the following discussion. All the mean coefficients are significantly estimated and have the expected signs. The standard deviations of all the coefficients are significant, indicating consumers are heterogeneous in responding to consumption, price, and holding cost. The mean of consumption coefficient $\bar{\phi}$ is positive, implying that consumption increases consumer benefit. Also, unit consumption benefit is higher for StarKist than for CKN. The risk coefficient $\bar{\gamma}$ is significantly positive implying a concave utility function and that consumers are risk averse. Consumers become saturated when consuming too much of a product. The coefficient of total price ($\bar{\alpha}$) indicates that total expenditure has a negative effect on utility. The coefficient of inventory ($\bar{h}$) implies that the higher the inventory, the lower the probability of purchasing because of the cost of storage.

4.3. Simulation

In this section, we use the estimated parameters of our proposed structural model as inputs for Monte

[13] We also estimated a model with last purchase, feature, and display as additional explanatory variables. This marginally affected the estimation and simulation without changing the main results.

Table 3b Model Estimation[a]

	Tuna category				
	Reduced form model		Structural model		
Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
Consumption benefit ϕ:					
StarKist	2.36	2.18	1.65	1.65	1.54
	(0.22[b])	(0.25)	(0.30)	(0.19)	(0.24)
	0.84	0.81	0.29	0.18	0.20
	(0.18)	(0.22)	(0.06)	(0.08)	(0.05)
CKN	1.25	1.01	0.64	0.60	0.65
	(0.19)	(0.32)	(0.19)	(0.21)	(0.21)
	1.14	0.82	0.20	0.19	0.18
	(0.22)	(0.21)	(0.09)	(0.07)	(0.07)
Risk aversion $\bar{\gamma}$:	−0.24	−0.37	−0.22	−0.21	−0.18
	(0.14)	(0.10)	(0.12)	(0.11)	(0.08)
	0.13	0.14	0.16	0.12	0.11
	(0.16)	(0.093)	(0.06)	(0.05)	(0.05)
Price $\bar{\alpha}$:	−4.01	−3.47	−2.99	−2.32	−2.18
	(0.52)	(0.15)	(0.29)	(0.41)	(0.31)
	0.89	−0.99	0.43	0.41	0.34
	(0.34)	(0.32)	(0.10)	(0.10)	(0.06)
Unit holding cost $\bar{h}$:			−0.036	−0.014	−0.062
			(0.022)	(0.021)	(0.012)
			0.030	0.012	0.044
			(0.017)	(0.022)	(0.016)
f[b]					
Purchase-incidence		0.010			
		(0.0091)			
Category preference β_0:	0.18	0.15			
	(0.08)	(0.06)			
	0.08	0.07			
	(0.03)	(0.03)			
Consumption rate β_1:	1.19	1.17			
	(0.19)	(0.18)			
	0.88	0.84			
	(0.44)	(0.41)			
Inventory β_2:	−0.13	−0.07			
	(0.04)	(0.03)			
	0.08	0.06			
	(0.08)	(0.04)			
Category value β_3:	0.38	0.34			
	(0.18)	(0.14)			
	0.57	0.53			
	(0.20)	(0.24)			
Purchase-quantity					
Quantity preference γ_0:	2.10	2.09			
	(0.45)	(0.44)			
	1.16	1.10			
	(0.20)	(0.19)			
Average quantity γ_1:	1.11	1.20			
	(0.34)	(0.29)			
	0.32	0.36			
	(0.06)	(0.13)			
Inventory γ_2:	−0.14	−0.12			
	(0.04)	(0.04)			
	0.06	0.04			
	(0.10)	(0.03)			
Price γ_3:	−3.01	−2.96			
	(0.79)	(0.83)			
	1.90	1.94			
	(0.26)	(0.22)			

[a]Standard errors are reported in parentheses.
[b]Parameter f is defined similarly as in Ailawadi and Neslin (1998).

Carlo simulations to explore the effect of promotion on consumption. Specifically, we are interested in using the model to derive the following implications: (1) How do purchase and consumption change differently with a price cut (Figure 2)? (2) Will consumption respond directly to promotion (Figure 3)? (3) How is consumption driven by inventory (Figure 4)? (4) How is the consumption-inventory relationship modified by holding cost and promotion uncertainty (Figure 4)? (5) How important is the consumption increase relative to brand switching and stockpiling (Tables 4 and 5)? (6) Can the proposed model be adopted to explain the absence of a post-promotion dip (Figure 5)?

In Figure 2, we randomly select week 10 (week 12) and cut prices for all sizes of StarKist tuna (Yoplait for yogurt) by 25%. We then plot the average purchases and average consumption of the promoted brand across consumers against time. The change of price in the promotion week will alter expected future prices. Comparing Figures 2a and 2b for tuna (Figures 2c and 2d for yogurt), we obtain the following results. First, it shows that consumption increases when there is a price promotion. This indicates that consumption is not constant. Second, a significant sales increase occurs in week 10 (week 12). There are some noticeable adjustments in the first two or three weeks (first two or three weeks) before sales go back to baseline sales after eight weeks (five weeks). Different from purchase, promotion causes consumption to increase significantly for three weeks (for two weeks). Consumption then gradually moves back to baseline level about nine weeks (four weeks) after the promotion. Allowing consumers to strategically make consumption decisions in light of promotion expectations, our dynamic model results in a smoother consumption path than the purchase path. This is because consumers are allowed to strategically decide not to consume everything available right away but instead to save for future consumption. Thus, how much to consume is optimally decided by consumers. Note the increase of consumption in the simulated promotion week is bigger for yogurt than for tuna. The promotion induced additional purchases are consumed at a faster pace for yogurt than for tuna. This indicates that promotion effect on consumption is bigger for product categories that are easily perishable.

In Figure 3, we plot average consumption across all consumers against various levels of permanent price changes (price cuts or price increases of x% in all periods). Since we assume consumers are aware of the fact that price changes are offered permanently, a forward-looking consumer is less likely to stockpile during promotion. Thus, most of the increase of consumption can be attributed to direct effect of promotion on consumption. When the price of StarKist (Yoplait)

Figure 2 **Purchase and Consumption Change with Promotion**

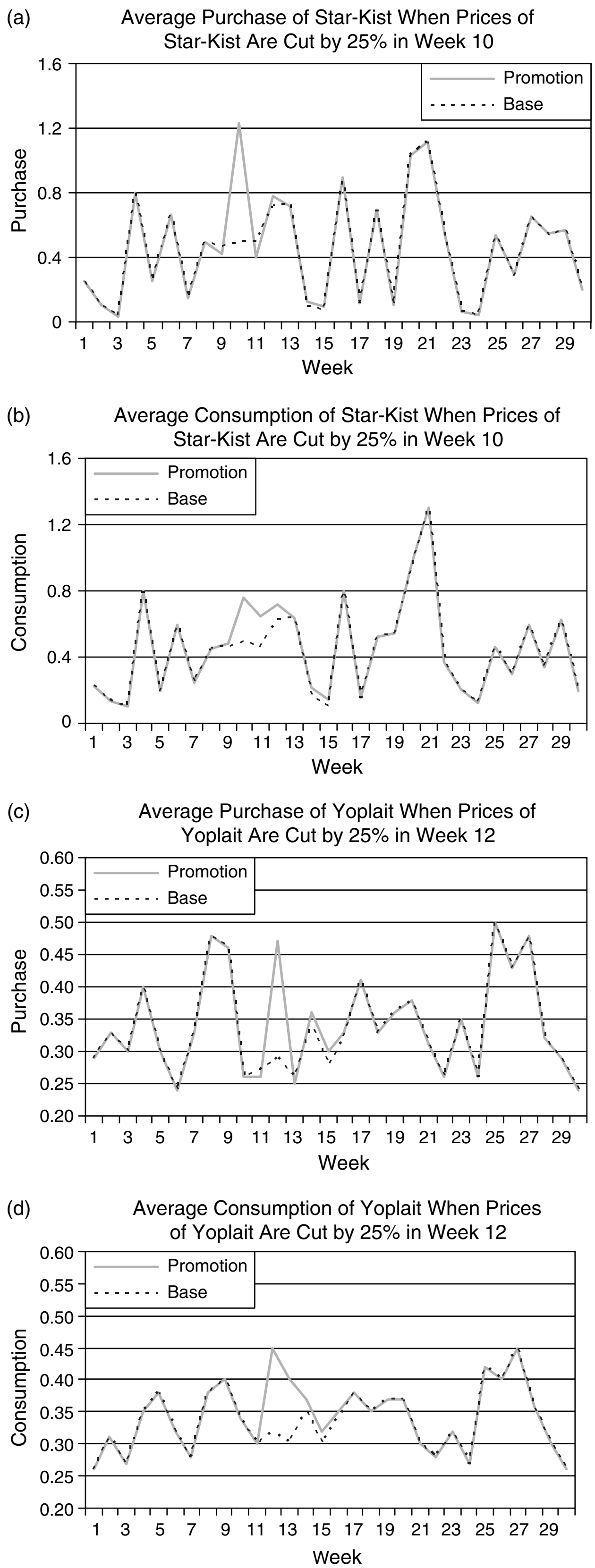
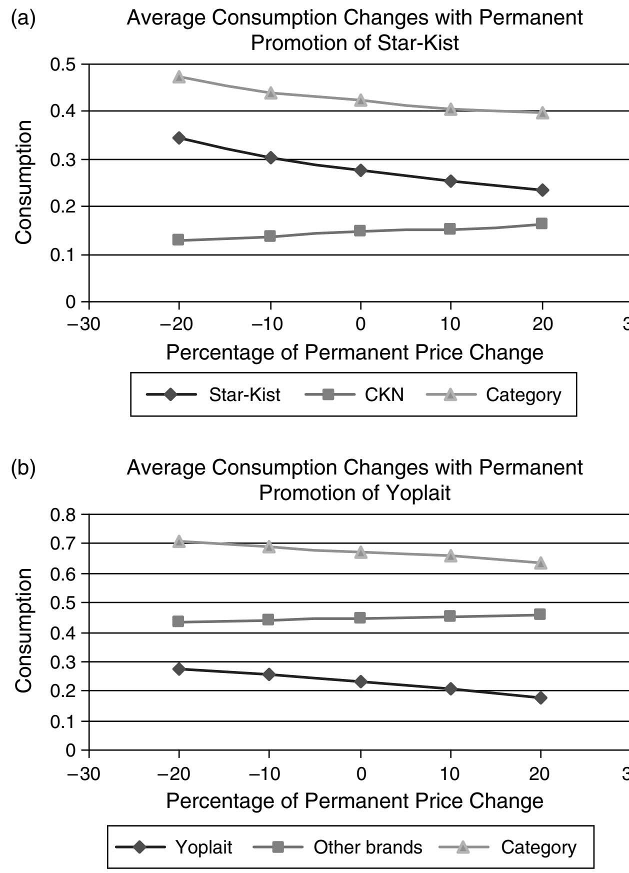


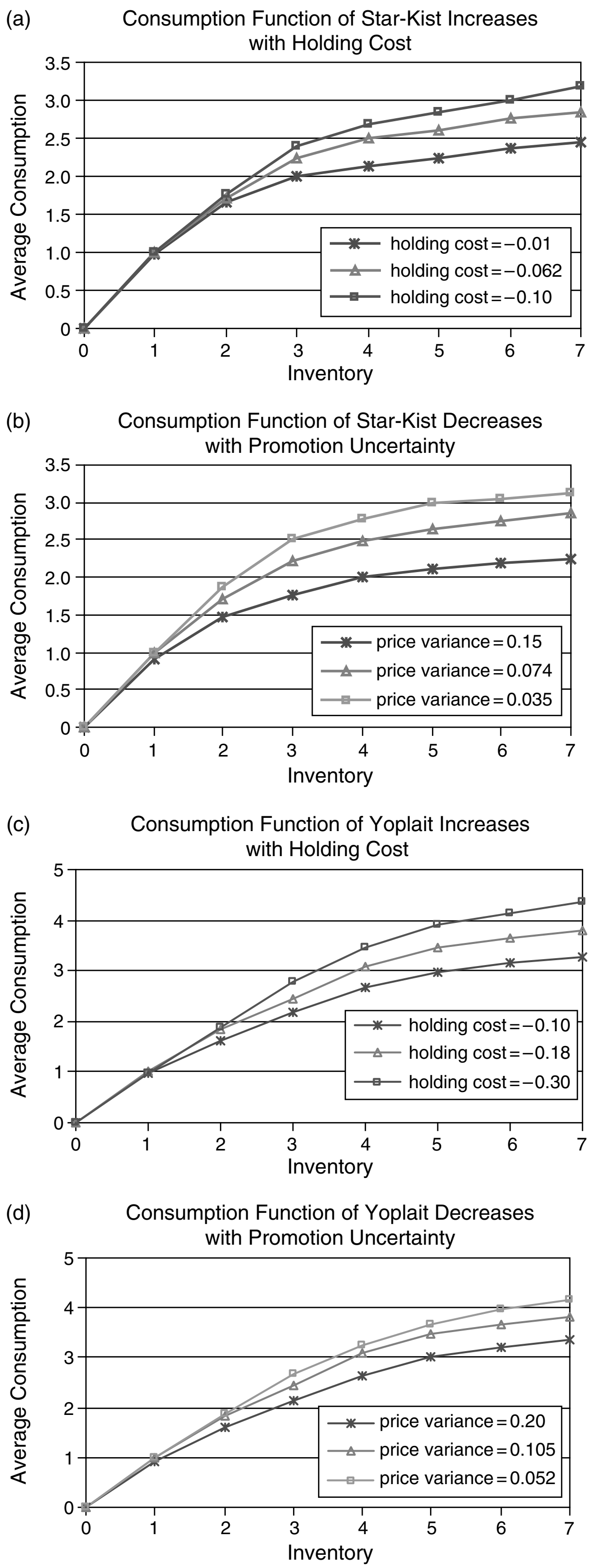
Figure 3 **Average Consumption Increases with Promotion**



drops for all periods, we find an increase of the average consumption of StarKist (Yoplait), but a decrease of the average consumption of CKN (other brands). Nevertheless, the average category consumption still increases. Our results indicate that average consumption could directly respond to price changes.

Figure 4a (Figure 4c) plots consumption (averaged across consumer and time) as a function of available inventories $(\sum_{j=1}^{J} I_{ijt-1} + \sum_{j=1}^{J} q_{ijt-1})$, which we define as consumption function. We plot the consumption function when the holding cost $(\bar{h})$ is 0.01, 0.062, and 0.10 for tuna (0.15, 0.074, and 0.035 for yogurt). It shows that consumption is an increasing function of inventory. How promotion induced stockpiling results in increased consumption is endogenously captured by our proposed model. It also shows that the consumption function increases with holding cost. The higher the disutility of holding inventory, the more consumers are willing to consume given the same inventory. Similarly, in Figure 4b (Figure 4d), we plot the consumption function for $\Sigma_{\eta_{11}} = 0.150$, 0.074, and 0.035 for tuna ($\Sigma_{\eta_{11}} = 0.200$, 0.105, and 0.052 for yogurt). The higher the uncertainty, the lower the consumption given the same inventory. In other words, the consumption function decreases with promotion uncertainty. Knowing that promotions are becoming

Figure 4 Consumption Function (Consumption Increases with Inventory)



less predictable, forward-looking consumers realize that the product might not be available at lower prices in the near future. They lower their current consumption and save for future demand given the same available inventory. Thus, given the same stockpiling, increased promotion uncertainty discourages a consumption increase.

To better understand promotion effect on contemporaneous sales, we break down the promotion sales increase in week 10 for tuna (week 12 for yogurt) into brand switching, consumption increase, and purchase displacement and report the results in Table 4. Brand switching is defined as the total units of CKN (Yoplait) consumers give up to purchase StarKist (the other yogurt brands) due to promotion of StarKist (Yoplait). These are purchases made by consumers who are expected to buy CKN (the other brands) without promotion but switch and buy the same amount of StarKist (Yoplait). Consumption change is defined as the difference between total consumption with promotion and total consumption without promotion in the week of promotion. The remaining part of the sales increase in the promotion week is defined as purchase displacement.

We report the breakdowns of the sales change in week 10 (week 12). We find that 33% (43%) of the sales increase is attributed to a consumption increase, 42% (39%) is due to brand switching, and 25% (18%) is from stockpiling as predicted by Model 5. Ignoring flexible consumption or stockpiling behavior, Models 1, 3, and 4 attribute the ignored consumption increase or stockpiling to brand switching. Model 2 also attributes a larger portion of the sales increase

Table 4 Breakdown of Promotion Effect on Short-Term Sales Increase

	Tuna category		
	Brand switching (%)	Consumption increase (%)	Purchase displacement (%)
Model 1	93	NA	7
Model 2	66	25	9
Model 3	60	40	NA
Model 4	52	NA	48
Model 5	42	33	25
	Yogurt category		
	Brand switching (%)	Consumption increase (%)	Purchase displacement (%)
Model 1	89	NA	11
Model 2	58	33	9
Model 3	54	46	NA
Model 4	53	NA	47
Model 5	39	43	18

Table 5 Consumption Elasticities

Tuna category		
	Consumption elasticities	
	StarKist	CKN
Model 1	NA	NA
Model 2	0.19	0.12
Model 3	0.35	0.25
Model 4	NA	NA
Model 5	0.29	0.19
Yogurt category		
	Consumption elasticites	
	Yoplait	Private label
Model 1	NA	NA
Model 2	0.25	0.18
Model 3	0.42	0.29
Model 4	NA	NA
Model 5	0.38	0.25

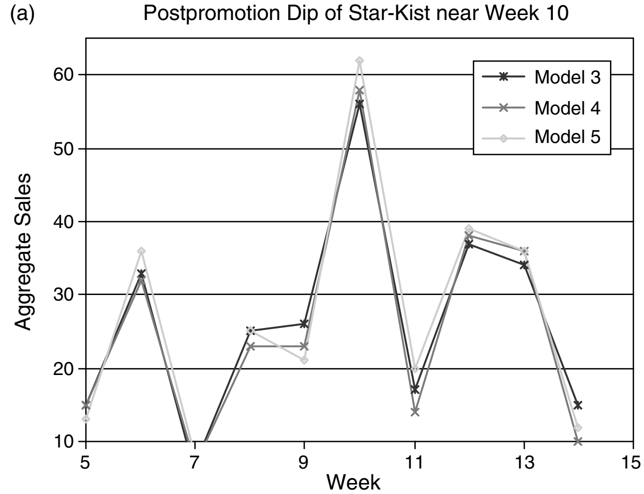
to brand switching.[14, 15] Consistent with our previous findings, consumption elasticity is higher for yogurt than for tuna.

To better demonstrate how promotion can stimulate current consumption, we also calculate consumption elasticities for the simulated promotion in week 10 for StarKist (week 12 for Yoplait) and compare the results with competing models. We report in Table 5 the percentage increase in consumption of the promoted brand given the 25% price promotion. The results confirm that Models 1, 2, and 4 underestimate promotion effect on consumption, and Model 3 overestimates this effect. We conduct a similar simulation for CKN (private label) and find the same result. We notice that consumption elasticity is higher for StarKist than for CKN (higher for Yoplait than for private label). This is because StarKist (Yoplait) is a stronger brand, and the benefits of consuming a preferred brand are greater than those of consuming a less preferred brand. Thus promotion has stronger impact on the consumption of stronger brands.

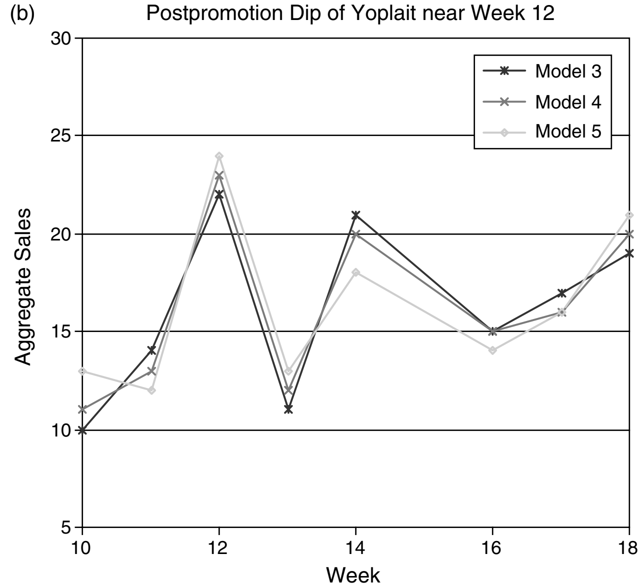
As an example of application, our model can be used to better understand why the postpromotion dip predicted by some conventional choice models is not significant using actual weekly sales from scanner panel data (Blattberg and Neslin 1990). In Figures 5a and 5b, we draw average weekly category sales against weeks and compare how average weekly category sales react to the simulated promotion using the three competing structural models. We focus on structural models because the underlying decision processes are known as opposed to reduced form models. As expected, the actual sales do not show a significant dip for both tuna and yogurt. Model 5 allows consumers to predict future promotions and optimally plan their purchases to coincide with promotion schedules. Consumers delay their

Figure 5 "Postpromotion" Dip

(a) Postpromotion Dip of Star-Kist near Week 10



(b) Postpromotion Dip of Yoplait near Week 12



[14] Consistent with van Heerde et al. (2003), we also find that ignoring category expansion leads to an overestimation of brand switching. However, our model can separate a consumption increase from brand switching and stockpiling, which cannot be achieved by existing models.

[15] We also calculate the breakdowns for all the periods following the promotion. We find that the sales change associated with a temporary promotion lasts for about eight weeks for tuna (5 weeks for yogurt), most of which is concentrated in the first two or three weeks. Using disaggregate model, we confirm the findings of Pauwels et al. (2003), who find that temporary promotion has an adjustment effect due to dynamic factors such as inventory, promotion expectation, consumption increase, stockpiling, etc. The permanent effect is not significant.

purchases until promotion, making sales before promotion relatively low. With more inventory, they also consume more, making the drop of sales after promotion less significant. Thus, for product categories with flexible consumption, the postpromotion dip could be insignificant because of the consumption effect at promotion and the purchase deceleration effect before promotion. Models 3 and 4 still result in a postpromotion dip because they ignore purchase deceleration and consumption increase, respectively.

Below we summarize the calibration results using the packaged tuna and yogurt.

- For products that are perceived to be versatile and substitutable, consumption is not constant but rather increases with inventory and promotion.
- The consumption function (consumption increases with inventory) increases as holding cost increases and promotion uncertainty decreases.
- Promotion not only causes brand switching and purchase acceleration but also stimulates consumption. Promotion has a stronger impact on the consumption of stronger brands.
- Conventional models assuming a constant or an exogenous consumption rate overestimate the importance of the brand-switching effect.
- Our simulation demonstrates that the lack of evidence for a postpromotion dip could be due to purchase deceleration before promotion and a consumption increase at promotion for product categories with flexible consumption.
- The dynamic structural model with endogenous consumption approximates the data the best. Thus, to measure promotion effect on sales accurately, it is important to treat consumers as rational agents who form promotion expectations and optimally adjust their purchase time and quantity as well as consumption to coincide with the promotion schedule.

Note the above empirical findings are drawn from the application of our proposed model to tuna and yogurt categories. When applying to other categories, these conclusion may be modified by the degree of consumption flexibility of those categories. We speculate that the higher the degree of flexibility of consumption, the bigger the effect of promotion on consumption.

5. Managerial Implications, Conclusion, and Future Research

Managers rely on periodic price promotions to stimulate demand, and this trend is expected to increase over time. If promotion simply induces brand switching and purchase displacement without encouraging consumption, promotion becomes a less effective strategy unless it can significantly attract new users from other stores or other categories. Conventional choice models cannot handle the promotion effect on endogenous consumption because they assume constant or exogenous consumption rates. It is important to understand how consumption responds to promotion. In this paper, we allow consumption to be a decision variable endogenously driven by promotion and propose a dynamic structural model with endogenous consumption under promotion uncertainty to examine the promotion effect on consumption. Based on this model, we investigate the issue whether promotion has any effect on consumption and provide insightful behavioral explanations on whether, why, and how consumption is affected by promotion.

Manufacturers usually initiate promotion to attract new users or brand switchers. Retailers frequently offer promotions to increase store sales. Applying the proposed model to tuna and yogurt data, we find some interesting empirical results that have important implications for manufacturers and retailers. First, managers should be aware that for product categories with versatile and substitutable consumption, promotion can encourage consumption in addition to brand switching and purchase displacement. Therefore, manufacturers should take into account the promotion effect on consumption when designing an optimal promotion strategy. Retailers should choose to promote categories whose consumption is most likely to increase without cannibalizing consumption of other categories. Second, because the increasing relationship between inventory and consumption is enhanced by holding costs, the consumption increases even more if retailers choose to promote product categories that are easily perishable or bulky.

Our analysis is subject to limitations which open avenues for future research. First, it will be interesting to apply our model to additional categories (e.g., candy, orange juice, pasta) and study explicitly how the promotion effect on consumption varies with the degree of flexibility of consumption. Second, retailers and manufacturers will be interested to know what type of consumers are more likely to consume more. Third, manufacturers and retailers initiate promotion for various reasons, e.g., attracting more shoppers, getting rid of inventory, creating demand of complementary categories. It will be interesting to study how to take advantage of the promotion effect on consumption to achieve those goals (e.g., Villas-Boas 2004). Fourth, we have focused on consumption of only one category. The model can be extended to multiple categories to study the cross-category effect of promotion on consumption. Finally, given the complexity of estimating a DP model, we have ignored other promotion variables such as coupon, feature, display, reference price, and brand loyalty, which will be interesting to explore in future research.

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