The Promotion Effect on Endogenous Consumption*

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Abstract

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 schedules. Applying the proposed model to packaged tuna, we find that endogenous consumption responds to promotion as a result of forward-looking and stockpiling behavior. This finding has important implications for managers who plan to better take advantage of the promotion effect on consumption. This is the first empirical paper that recognizes consumption as an endogenous decision variable and proposes a structural model, which offers behavioral explanations on whether, how and why promotion encourages consumption for product categories with elastic consumption.

Keywords: Promotion, Consumption, Category Expansion, Dynamic Structural Model, Forward-looking Consumers

1 Introduction

Does consumption respond to promotion? Many studies have focused on the effects of promotion on brand switching, purchase quantity and stockpiling, and 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, Briesch and Fox 1995). Conventional choice models can not be used to address this issue since 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 may not hold for many other product categories like 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, Martin and Gupta (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

[1] For disaggregate models, see Guadagni and Little (1983), Gupta (1988), Bucklin and Lattin (1991), Chintagunta (1993), Krishna (1994b), Chiang (1995), Bucklin, Gupta and Siddarth (1998), Bell, Chiang and Padmanabhan (2000), Seethraman (2003), Neslin, Henderson and Quelch (1985), Mela, Jedidi and Bowman (1998), and Kopalle, Mela and Marsh (1999), among others. For aggregate models, see Mela, Gupta and Jedidi (1998), Mela, Jedidi and Bowman (1998), Kopalle, Mela and Marsh (1999), Dekimpe, Hanssens and Silva-Risso (1999), Paap and Franses (2000), Nijs, Dekimpe and Steenkamp (2001) and Pauwels, Hanssens and Siddarth (2002), etc.

study, Assuncao and Meyer (1993) show that consumption is an endogenous decision variable driven by promotion and promotion-induced-stockpiling, which results from forward-looking behavior.

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 optimization problems 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.[2] In this paper, we develop a forward looking structural model which 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 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.

Applying our model to packaged tuna data, our analysis sheds new insights on the following issues which can not 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, Briesch and Fox 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 "post promotion" dip?

[2] See Rust (1985) for more information.

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 and Krishna 1992). Assuncao and Meyer (1993) advance existing theoretical models 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, Tang and Bell (1998) show that the average optimal consumption rate increases with price fluctuation. Bell, Iyer and Padmanabhan (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, Imai and Keane (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, Neslin and Srinivasan (2003) demonstrate that ignoring forward looking behavior leads to an overestimation of promotion elasticity. However, the frameworks developed in these papers cannot be adopted to study the promotion effect on consumption because they assume constant or exogenous consumption, which is independent of promotion.[4]

[3]Erdem, Imai and Keane (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 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. In order 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, Neslin and Srinivasan (2003) in modeling inventory and price process. This significantly reduces the computational burden and offers us the flexibility to endogenize consumption.

[4]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 can not 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 over-estimated if we ignore dynamics. On the contrary, in our model, consumers solve

The only published empirical paper that studies the promotion effect on consumption is Ailawadi and Neslin (1998) which adopts a 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 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. (3) It provides more reliable simulation results because it is not subject to the "Lucas Critique."

3 Dynamic Model with Endogenous Consumption under Promotion Uncertainty

3.1 Model Setup

3.1.1 Consumption Utility

Suppose consumers $i = 1, \cdots, I$ visit stores on a periodic, e.g., weekly basis for $t = 1, \cdots, T$. In the store, there are $j = 1, \cdots, J$ competing brand choices in addition to the default non-purchase choice $j = 0$. Each consumer observes prices and promotions for all the competing brands in a product category of interest.[5] 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

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.

[5]In the following discussion, we do not explicitly differentiate price and promotion. We refer to the change of price as price promotion. Since 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, Imai and Keane (2003).

per period utility function at time t:[6]

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

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. Since 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.[7]

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

where a dummy variable $d_{jqt} = 1$ denotes a purchase of brand j and quantity q.[8]

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

[6] 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 section 3.2.

[7] We include inventory costs in the budget constraint. This is equivalent to including inventory costs directly in the utility function. See Erdem, Imai and Keane (2003) and Sun, Neslin and Srinivasan (2003) for a similar treatment of inventory cost.

[8] 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.

And 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 obtain the following expression for the per period utility function:

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

To simplify the notations, we define $I_t = \sum_{j=1}^{J} I_{jt}$ as the category inventory at time t. Moreover, since 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.

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.

$$Max_{c_{jt}, d_{jqt}} E_t \{ \sum_{\tau=t}^{\infty} \delta^{\tau - t} (U_\tau + \epsilon_\tau) \}. \tag{7}$$

The variable δ is the discount factor, which reflects 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:

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

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}. We let D_t denote the vector of decision variables at time t, which include the brand-quantity choice and the consumption choice. Following equation (8), the optimal consumption maximizes the value function given the optimal brand-quantity decision, d^*_{jqt}:

$$c^*_{jt} = \text{argmax}_{c_{jt}}\{V(F_t) = \sum_{j=1}^{J} \phi_j(c_{jt} - \gamma c_{jt}^2) - \alpha \sum_{j,q} d^*_{jqt}P_{jt}q_{jt} - hI_t + \epsilon_t + \delta E[V(F_{t+1})|F_t]\}. \tag{9}$$

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. 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 $\delta E[V(F_{t+1})|F_t]$ and thus changes the relative tradeoffs between current and future consumption. The indirect effect of the 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 the inventory level and prices.

3.1.4 Store Visits

In the data, we observe that consumers sometimes do not visit the store. If a consumer visits the store, her behavior is described by the above model. If she does not visit the store, she only chooses consumption and does so as 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 an extra precautionary incentive to hold inventories. Consumption also varies with duration between visits.

We use a binomial distribution to model store visit behavior.[9] 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:

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

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

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,

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

[9] Hendel and Nevo (2002) also use binomial distribution to model store visits.

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:

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

Competitor reaction is captured by entering the mean price of all competing brands in the price process. The diagonal elements denote the corresponding variance of η_j and the off diagonal elements denote the covariance between the 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:

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

where I_1 denotes the initial inventory and $D_{it}^h = (D_{i1}, ..., D_{it})$ denotes the history of $D_{i\tau}$ for τ from 1 up to t. Similarly, $S_{it}^h = (S_{i1}, ..., S_{it})$ 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:

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

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, and V_{ijqt} is the value function for choice j, q for consumer i at time t and is given by:

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

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. Due to 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.[10]

[10] We would like to point out three issues in the empirical application. First, since 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 2 brands in the 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 times to simulate the initial inventory distribution for a consumer.

4 Empirical Application

4.1 Data Description

[Insert Table 1 About Here]

We use Lite Tuna data collected by the A. C. Nielsen Company and focus on purchases of the two leading brands which comprise more than 93% of the market share, namely, Star-Kist and Chicken-of-the-Sea (CKN). The calibration sample consists of 6200 observations from 50 randomly selected households during 124 weeks from 1986 to 1988 in Sioux Falls. The 50 households made 839 purchases of Tuna during the observation period. Table 1 reports the descriptive statistics. The average purchases per incidence are 2.77 and 2.57 cans of 6.5oz for Star-Kist and CKN. Consumers' average consumption per week for Star-Kist and CKN is 0.48 and 0.31 cans of 6.5oz tuna, respectively. Consumers sometimes buy more tuna than their average consumption. We reserve 980 observations from 49 households over the course of 20 weeks who made 145 purchases of tuna in Springfield for cross sample validation.

4.2 Estimation and Comparison

[Insert Table 2 About Here]

We will compare our dynamic structural model with four baseline models. 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, Neslin and Srinivasan (2003) and Erdem, Imai and Keane (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, 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 explicitly determine their future consumption in light of inventory and promotion.

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 the 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 seems remarkably good on all these dimensions, indicating that the proposed model "approximates" the data very well.

[Insert Table 3 About Here]

Table 3a reports the maximum likelihood estimates of the parameters in the price process. Most of the coefficients are significantly estimated except that of time trend and covariance. The coefficient of the average of competitors' price is positive and significant implying that StarKist increases its price if the average last period price of competitors is higher. The covariance between Star-Kist 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, Imai and Keane (2003).

In Table 3b, we report the estimation results of the five competing models with the mean parameter estimates reported in the first line and the standard deviation estimates across households reported in the second line.[11] We follow the convention and fix the weekly

[11]We also estimated a model with last purchase, feature and display as additional explanatory variables.

discount factor at 0.995. Since 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 that consumers are heterogeneous in responding to consumption, price and holding cost. The mean of the consumption coefficient $\bar{\phi}$ is positive implying that consumption increases consumer benefit. Moreover, the unit consumption benefit is higher for Star-Kist 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 due to the cost of storage.

4.3 Simulation

In this section, we use the estimated parameters of our proposed structural model as inputs for Monte-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 1) (2) Will consumption responds directly to promotion? (Figure 2) (3) How is consumption driven by inventory? (Figure 3a and 3b)(4) How is the consumption-inventory relationship modified by holding cost and promotion uncertainty? (Figures 3a and 3b) (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 4)

[Insert Figure 1 About Here]

In Figure 1, we randomly select week 10 and cut prices for all sizes of the leading brand, Star-Kist, by 25% and plot the average purchases and average consumption across consumers against time. The change of price in week 10 will alter expected future prices. Comparing Figure 1a and 1b, we obtain the following results. First, it shows that consumption increases

This marginally affected the estimation and simulation without changing the main results.

when there is a price promotion. This indicates that consumption is not constant. Second, a significant sales increase occurs in week 10. There are some noticeable adjustments in the first 2 or 3 weeks before sales go back to baseline sales after 8 weeks. Different from sales, promotion causes consumption to increase significantly for 3 weeks. Consumption then gradually moves back to the baseline level about 9 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.

[Insert Figure 2 About Here]

In Figure 2, we consider permanent price changes (price cuts or price increases of x% in all periods) and determine the resulting average consumption across all consumers. 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 the direct effect of promotion on consumption. When the price of StarKist drops for all periods, we find an increase of the average consumption of StarKist, but a decrease of the average consumption of CKN. Nevertheless, the average category consumption still increases. Our results indicate that average consumption directly responds to price changes.

[Insert Figure 3 About Here]

Figure 3a 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 the consumption function. We plot the consumption function when the holding cost ($\bar{h}$) is 0.01, 0.064 and 0.10. It shows that consumption is an increasing function of inventory. How promotion induced stock-piling 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 3b, we plot the consumption function for $\Sigma_{\eta_{11}} = 0.150, 0.071$ and 0.035. 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 less predictable, forward looking consumers realize that the product may 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.

[Insert Table 4 About Here]

In order to better understand the promotion effect on contemporaneous sales, we break down the promotion sales increase in week 10 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 consumers give up to purchase Star-Kist due to the promotion of Star-Kist. These are purchases made by consumers who are expected to buy CKN without promotion but switch and buy the same amount of Star-Kist. 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. We find that 33% of the sales increase is attributed to a consumption increase, 42% is due to brand switching, and 25% is from stockpiling as predicted by Model 5. Ignoring elastic consumption or stockpiling behavior, Models 1, 3 and 4 attribute the ignored consumption increase or stockpiling to brand switching.[12] Model 2 also attributes a larger portion of the sales increase to brand switching.[13]

[Insert Table 5 About Here]

[12]Consistent with Van Heerde, Gupta, and Wittink (2003), we also find that ignoring category expansion leads to an over-estimation of brand switching. However, our model can separate a consumption increase from brand switching and stockpiling, which can not be achieved by existing models.

[13]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 8 weeks, most of which is concentrated in the first 2 or 3 weeks. Using disaggregate model, we confirm the findings of Pauwels, Hanssens and Siddarth (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.

To better demonstrate how promotion can stimulate current consumption, we also calculate consumption elasticities for the simulated promotion in week 10 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 the promotion effect on consumption and Model 3 overestimates this effect. We conduct a similar simulation for CKN and find the same result. We notice that consumption elasticity is higher for Star-Kist than for CKN. This is because Star-Kist is a stronger brand and the benefits of consuming a preferred brand are greater compared to those of consuming a less preferred brand. Thus promotion has stronger impact on the consumption of stronger brands.

[Insert Figure 4 About Here]

As an example of application, our model can be used to better understand why the "post promotion" dip predicted by some conventional choice models is not significant using actual weekly sales from scanner panel data (Blattberg and Neslin 1990). In Figure 4, we predict how average weekly category sales react to the simulated promotion in week 10 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. Model 5 allows consumers to predict future promotions and optimally plan their purchases to coincide with promotion schedules. Consumers delay their 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 "post promotion" dip could be insignificant due to the consumption effect at promotion and the purchase deceleration effect before promotion. This provides some empirical evidence for two of the nominal explanations (i.e. purchase deceleration and consumption increase) of the nonexistence of a "post promotion" dip provided by Neslin and Stone (1996). Model 3 and 4 still result in a "post promotion" dip because they ignore purchase deceleration and consumption increase, respectively.

Below we summarize the calibration results using the packaged tuna data:

- 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 "post promotion" dip could be due to purchase deceleration before promotion and a consumption increase at promotion for product categories with elastic consumption.

- The dynamic structural model with endogenous consumption approximates the data the best. Thus, in order to measure the 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 the tuna category. When applying to other categories, these conclusions 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 can not 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.

Manufactures usually initiate promotion in order to attract new users or brand switchers. Retailers frequently offer promotions in order to increase store sales. Applying the proposed model to tuna data, we find some interesting empirical results that have important implications for manufacturers and retailers. First, mangers should be aware of the fact 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, since the increasing relationship between inventory and consumption is enhanced by holding costs, consumption increases even more if retailers choose to promote product categories that are easily perishable or bulky. Third, in order to benefit the most from the promotion effect on consumption, *ceteris paribus*, retailers can choose to promote stronger brands (usually higher priced) which will lead to a higher consumption increase.

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, yogurt) and study explicitly how the promotion effect on consumption varies with the degree of flexibility of consumption. Second, retailers and manufactures will be interested to know what type of consumers are more likely to consume more. Third, manufactures 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 in order to achieve those goals. Fourth, we have focused only on consumption of one category. The model can be extended to multi-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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Table 1. Descriptive Statistics

Brands	Market Share	Ave Price Per oz	Average Purchase Quantity (6.5oz)
Star-Kist	67.73	0.111	2.77
6.5oz	57.68	0.100	
13oz	10.05	0.110	
CKN	32.27	0.104	2.57
6.5oz	27.34	0.094	
13oz	4.93	0.117	

Table 2a. Model Comparison

Model fit statistics	Reduced Form Models		Structural Models		
	Model 1	Model 2	Model 3	Model 4	Model 5
Calibration Sample[a]					
-Log-Likelihood	6659.0	6627.1	6620.2	6609.2	6575.8
AIC	6687.0	6656.1	6630.5	6619.2	6585.8
BIC	6781.3	6753.7	6663.9	6652.9	6619.5
Holdout Sample[b]					
-Log-Likelihood	1035.2	1004.2	1000.1	992.2	957.3
AIC	1063.2	1033.2	1010.1	1002.2	967.3
BIC	1131.6	1104.1	1034.6	1026.7	991.9

a. Number of households=50; Number of weeks=124; Number of observations=6200.
b. Number of households=49; Number of weeks=20; Number of observations=980.

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

	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
Star-Kist	9.52	11.26	11.13	10.01
CKN	4.37	4.00	3.88	4.20
Average Purchase Quantity				
Star-Kist	2.77	2.80	2.79	2.75
CKN	2.57	2.55	2.56	2.61

Table 3a. Estimates of the Price Process

Parameter	**Estimates**
Brand constant λ_1: Star-Kist	-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)

Table 3b. Model Estimation [a]

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

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

Figure 1. Purchase and Consumption Change with Promotion

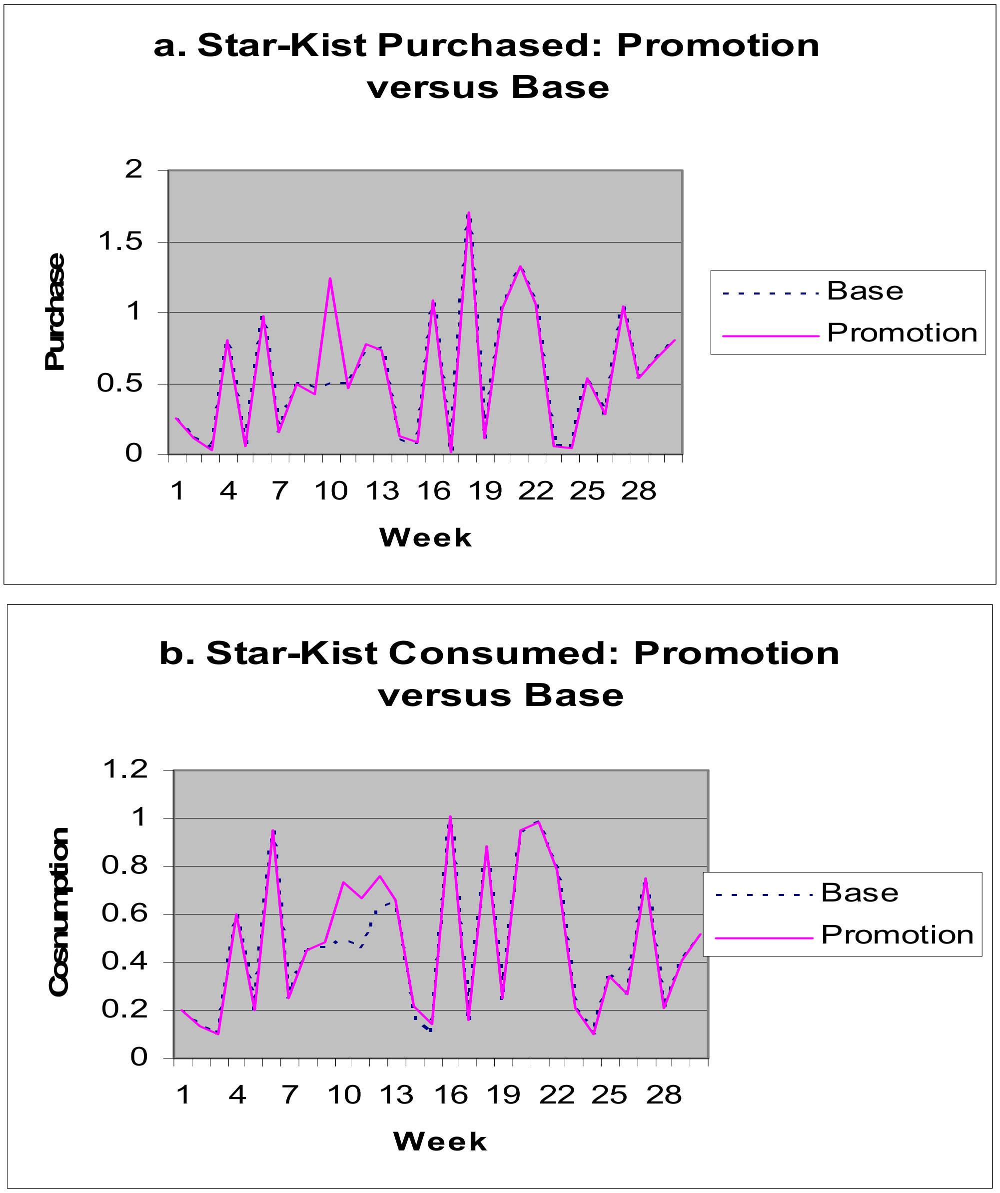


Figure 2. Average Consumption Increases with Promotion

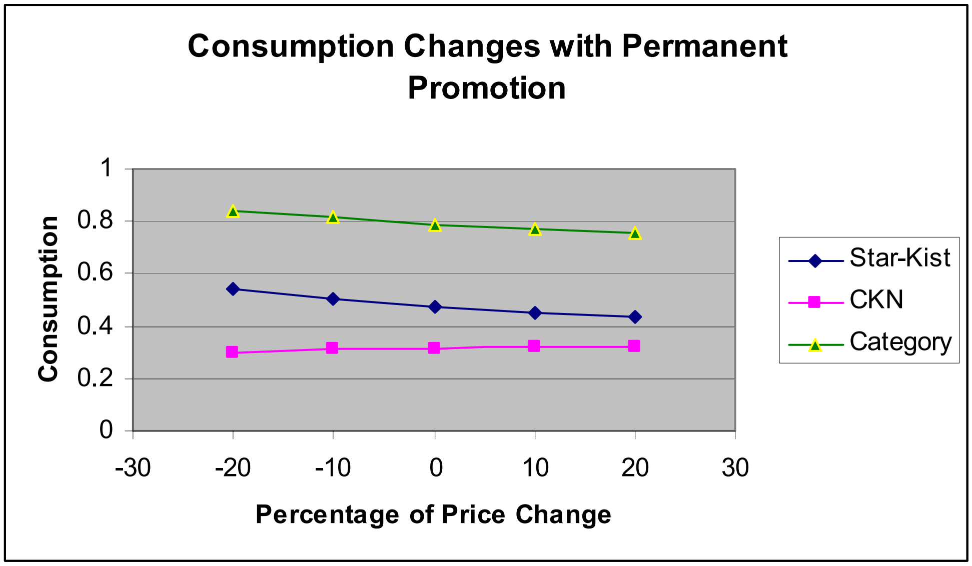
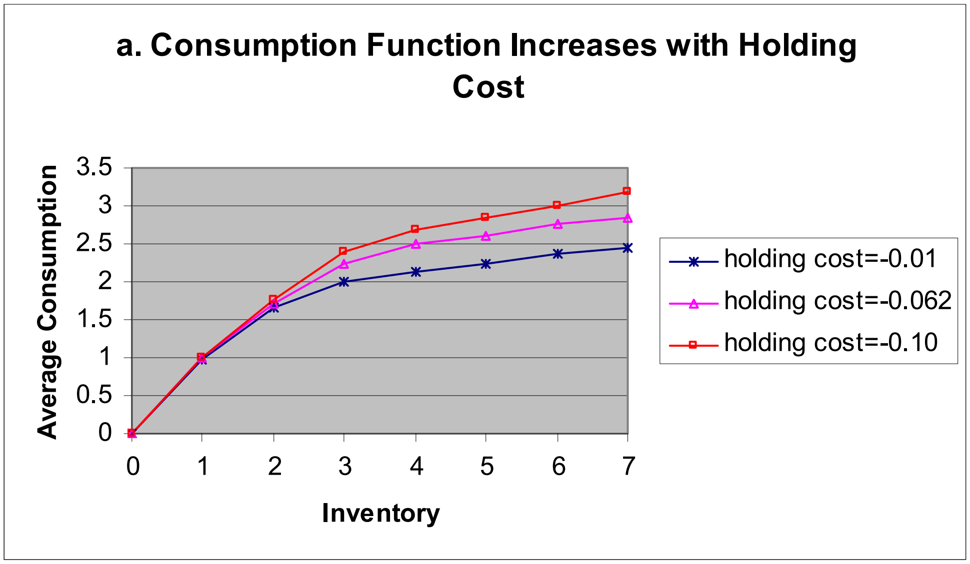


Figure 3. Consumption Function
(Consumption Increases with Inventory)



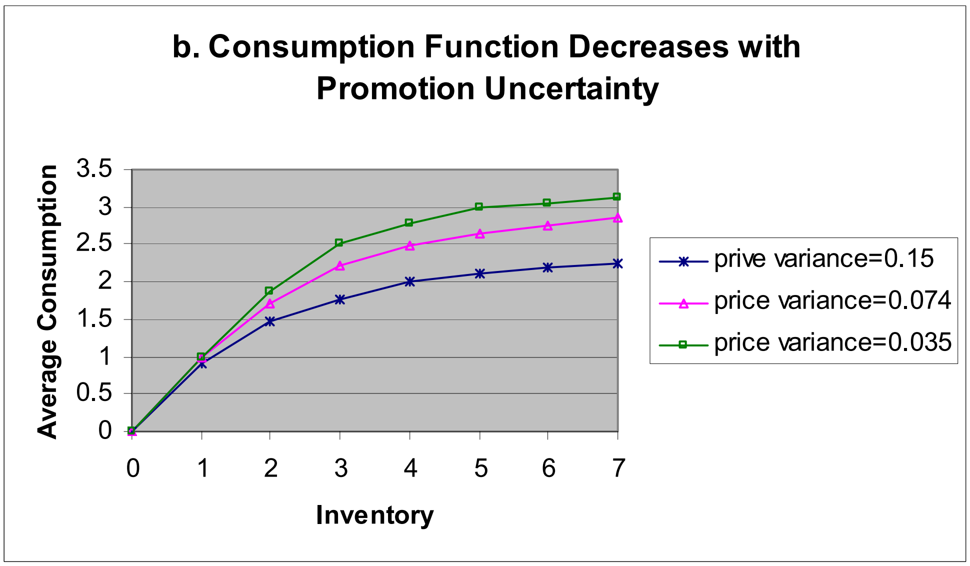


Table 4. Break-down of Promotion Effect on Short-term Sales Increase

	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%

Table 5. Consumption Elasticities

	Consumption Elasticities	
	Star-Kist	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

Figure 4. "Post Promotion" Dip