A Model of Purchase Behavior under Price Uncertainty: A Real Options Approach

Hiroto Suzuki\textsuperscript{a,†} Makoto Goto\textsuperscript{b} Takahiro Ohno\textsuperscript{a}

\textsuperscript{a}Graduate School of Creative Science and Engineering, Waseda University
\textsuperscript{b}Graduate School of Economics and Business Administration, Hokkaido University

Abstract: Retailers, such as discount stores and supermarkets, frequently conduct price promotions, and promotions for stockable products are particularly frequent. In that category, consumers tend to purchase at a lower price and postpone purchasing at a higher price. That is, they make a decision to purchase or postpone purchasing according to their memories of past prices and the current price. In the other words, under price uncertainty, they make their purchase decision by considering the option value of postponing purchase. Therefore, we develop a consumer purchase incidence model and brand choice model considering the postpone option by using a real options approach.

Keywords: Purchase incidence; Brand choice; Real options; Logit model

\textsuperscript{*}Received: July 30, 2015; Accepted: October 10, 2015.
\textsuperscript{†}Corresponding author. Address: 3-4-1 Okubo, Shinjuku-ku, Tokyo 169-8555, Japan; Phone: +81-3-5286-8042; E-mail: hiroto-suzuki@aoni.waseda.jp
1 Introduction

There have been many studies about consumer purchase behavior and price promotion. Retail stores, especially discount stores and supermarkets, run sales promotions to increase store traffic and sales for a specific category or product. There are two kinds of strategies of price promotion, one is EDLP (EveryDay Low Price), and the other one is Hi-Lo, which switches to the promotion price from the usual price. These price promotions affect consumer purchase behavior, and thereby also retail stores’ profits. Therefore, much research about consumer purchase behavior and price promotion has been carried out, because of their importance.

In many studies, the focus is on consumer purchase incidence and brand choice. Purchase incidence refers to whether a consumer purchases the category or not at a purchase opportunity, and brand choice refers to which product a consumer purchases from the category at the purchase opportunity. Actually, many consumer psychological and decision processes occur before a purchase takes place, but Guadagni and Little [8], Gupta [9], and Gupta [10] showed that price promotion strongly affects purchase incidence and brand choice, and they are thus the focus of many studies. In these studies, nested logit models are used because the relationship between the two decision processes in the model can be considered, and it is easy to estimate the parameters.

We propose here a new nested logit model of consumer purchase incidence and purchase behavior. The purchase incidence model is constructed so as to calculate the value of postponing purchase by a real options approach. In many cases, retail stores run price promotions irregularly; thus, for consumers, the price can be treated as uncertain. Moreover, Sun et al. [17], Erdem et al. [7] showed that for a stockable category of products, for example tissue paper and shampoo, consumers tend to purchase if the price is low; otherwise, they postpone their purchases until they are out of inventory. In the other words, consumers remember the previous price and try to maximize their purchase utility through their decision to purchase or not under uncertainty. It can be considered that they make their purchase decision according to the value of postponing the purchase. The real options approach mentioned above is an approach in option theory applied to a real asset in order to calculate its value. In particular, the real options approach allows the value postponing an irreversible investment to be calculated under uncertainty. Since in consumer the purchase behavior considered, there is purchasing under price uncertainty and most purchases are irreversible, we apply the real options approach to the problem of calculating the value of postponing purchase in our purchase incidence model.

In this paper, we first focus on purchase incidence. The following are some of the studies on purchase incidence reported in the literature: Bucklin and Lattin [4] and Bucklin and Gupta [5] used a nested logit model structure to propose a purchase incidence and brand choice model; Sun et al. [17] and Erdem et al. [7] used a dynamic structure model. The dynamic structure model can be considered with uncertainty, but this makes the parameter estimation difficult because the Markov chain Monte Carlo method is required. Compared with a nested logit model, much time is needed to estimate parameters. These previous studies used a nested logit model for which parameter estimation was easier, but did not consider uncertainty. Based on Bucklin and Lattin [4], Bucklin and Gupta [5] and some studies proposed a model of purchase amount.

We will next focus on consumer purchase behavior and reference price. Consumers remember previous prices and they have “rough” prices for each product or category. When consumers consider
the actual current price, they compare it with the rough price at the time of purchase decision. The reference price is such a rough price that consumers remember upon purchase. When consumers consider the actual current price, they compare it with a reference price at the time of purchase decision. Lattin and Bucklin [13] treated the reference price as a weighted average of past prices, Rajendran and Tellis [15] treated it as a geometric average, and Bell and Bucklin [1] treated it as the price at the last purchase opportunity. However, on these approach also, uncertainty cannot be considered.

Taking a real options perspective, we incorporate the uncertainty of decision-making into the model. While managers decide to invest “absolutely” under price/demand uncertainty in a real options model, consumers decide to purchase “randomly” under uncertainty of utilities in a marketing science model. There are few reports in the literature of attempting to incorporate a real options perspective into a marketing science model. Haenlein et al. [11] evaluate the real option of abandoning unprofitable customers by using customer lifetime value. Boyd and Brown [3] analyze marketing control right distribution decisions as a real option by using a logit model. Ziedonis [18] and Jiang et al. [12] also use logit models so as to evaluate a licensor’s option to invest in market entry itself or to allow the licensee to undertake market entry investments. However, Haenlein et al. [11] do not incorporate the uncertainty of decision-making, and the other studies do not calculate options values appropriately for the real options approach. To the best of our knowledge, no studies have incorporated uncertainty of decision-making into a real options model in an appropriate way.

In this paper, we propose a model of purchase incidence and brand choice based on the nested logit model of Bucklin and Gupta [5], considering price uncertainty by a real options approach. We show that it is possible to consider the uncertainty in the nested logit model, and our model achieves a better fit than that of Bucklin and Gupta [5]. This is the first attempt to combine a real options model and a consumer behavior model.

2 The Model

We construct a model of purchase incidence and brand choice under uncertainty, based the nested the logit model of Bucklin and Gupta [5], for which it is easy to calculate parameters. Especially in the case of stockable products, consumers make purchase decisions by considering the value of being able to purchase at a lower price by postponing purchase. We construct a model to calculate the value of postponing a purchase on purchase incidence. The value of postponing purchase can be calculated from the future price and the transition probability by a real options approach. Sun et al. [17] and Erdem et al. [7] showed that consumers remember the frequency of price promotions and the prices, so we construct such a price transition model and estimate the parameters. In this construction, we use the same brand choice model and estimation method, the maximum likelihood approach, as used in Bucklin and Gupta [5]. Furthermore, we estimate the parameters in the purchase incidence model by maximum likelihood method via backward induction.

2.1 Purchase Incidence and Brand Choice Models

It is very inconvenient to us as consumers when we are out of a stockable product, and so we try to purchase so as to never be out of inventory. In the other words, our personal amount of inventory
affects our purchase behavior. The out-of-inventory date can be estimated from the current amount of inventory and the average rate of consumption. Therefore, based on Bucklin and Gupta [5], consumer $h$’s amount of inventory $INV^h_t$ at the time $t$ is given by

$$INV^h_t = INV^h_{t-1} + Q^h_{t-1} - CR^h;$$ (1)

where $Q^h_{t-1}$ is consumer $h$’s amount of purchase at time $t-1$, and $CR^h$ is consumer $h$’s average rate of consumption. We focus on the interval between one purchase and the next purchase.

We define the time of being out of inventory as time 0; then consumer $h$’s estimated time until out of inventory $T^h$ is given by

$$T^h = \frac{INV^0_h}{CR^h};$$ (2)

Thus, the estimated time until out of inventory at $t$, $\tau^h_t$, is given by

$$\tau^h_t = \frac{INV^h_t}{CR^h}, \quad 0 \leq \tau^h_t \leq T^h.$$ (3)

We truncate the values of $T^h$ and $\tau^h_t$ to the first decimal place because our model is discrete.

Next, based on Bucklin and Gupta [5], we can define by a nested logit model consumer $h$’s probability of purchasing brand $i$ at $t$ as

$$P^h_t (i) = P^h_t (inc) \cdot P^h_t (i|inc),$$ (4)

where $P^h_t (inc)$ is the probability of purchase incidence and $P^h_t (i|inc)$ is the probability of a particular brand choice for brand $i$ ($= 1, 2, \ldots, n$). The probability of brand choice $P^h_t (i|inc)$ is defined by a multinomial logit model:

$$P^h_t (i|inc) = \frac{\exp (U^h_{i,t})}{\sum_{j=1}^{n} \exp (U^h_{j,t})}.$$ (5)

We define consumer $h$’s deterministic utility $U^h_{i,t}$ and random utility $\tilde{U}^h_{i,t}$ for brand $i$ at $t$ as

$$U^h_{i,t} = u^i + \beta X^i_t,$$ (6)

$$\tilde{U}^h_{i,t} = U^h_{i,t} + \varepsilon^h_{i,t},$$ (7)

where $u^i$ is the characteristic value of brand $i$, $\beta$ is a vector of coefficients, and $X^i_t$ is a vector of marketing variables. The marketing variables are in general 0-1 variables which denote the existence of promotions in retail stores, such as price promotion, special display, and point of purchase advertisement. We define $\varepsilon^h_{i,t}$ as having the Gumbel distribution.

Consumers make their purchase decisions by comparing the utility of purchasing versus not purchasing. In the purchase incidence model, we construct the decision model. In the case where retail stores don’t have price promotions, consumers get the chance to purchase at a lower price, and so they do not purchase now. In this case, the utility of non-purchase includes the value of postponing purchase. Therefore, the probability of purchase incidence $P^h_t (inc)$ is defined by a binomial logit model as

$$P^h_t (inc) = \frac{\exp (W^h_{1,t})}{\exp (W^h_{0,t}) + \exp (W^h_{1,t})}.$$ (8)
Consumer h’s deterministic utility of purchase $W_{1,t}^h$ at $t$, random utility of purchase $\tilde{W}_{1,t}^h$, deterministic utility of non-purchase $W_{0,t}^h$, and random utility of non-purchase $\tilde{W}_{0,t}^h$ are defined as

$$W_{1,t}^h = \pi_{1,t} + \theta_{1,t} \cdot CV_t^h,$$

$$\tilde{W}_{1,t}^h = W_{1,t}^h + \epsilon_{1,t},$$

$$W_{0,t}^h = \pi_{0,t} + \theta_{0,t} \cdot OV_t^h,$$

$$\tilde{W}_{0,t}^h = W_{0,t}^h + \epsilon_{0,t},$$

respectively, where $\pi_{1,t}$ and $\pi_{0,t}$ are the characteristic values of purchase and non-purchase, respectively; $\theta_{1,t}$ and $\theta_{0,t}$ are vectors of coefficients; $\epsilon_{1,t}$ and $\epsilon_{0,t}$ are defined as having the Gumbel distribution; $CV_t^h$ is the category value

$$CV_t^h = \ln \sum_{j=1}^{n} \exp (U_t^{h,j}),$$

and $OV_t^h$ is the value of postponing purchase, which is given in the next subsection. When the price is lower, consumers tend to purchase and increase their inventory. Therefore, they consider the probability of purchasing at lower price at a later date and postpone purchase, especially for the stockable product category. We can say consumers make their decision in consideration of the value of postponing purchase.

### 2.2 Option Values

We construct a model to calculate the option value $OV_t^h$ under price uncertainty for consumer $h$ at $t$ by a real options approach. Specifically, consumers obtain the utility of the category value $CV_t^h$ upon purchase, and otherwise obtain the option value of postponing purchase $OV_t^h$. Here, we define the option value of postponing purchase so that consumers obtain the expected utility at their next purchase opportunity in the case of postponing purchase.

Retail store price promotions are frequent but irregular, so the timing is unknown for consumers. Therefore, the price moves up and down randomly from the consumer viewpoint. Since stockable products are sold at a promotion price and a usual price, we define brand $i$’s price at $t$, $Y_i^t$, by a binomial model similar to that of Sun et al. [17]:

$$Y_i^t = \bar{Y}_i^t - x_i^t D^t \bar{Y}_i^t,$$

where $\bar{Y}_i^t$ is the usual price, $x_i^t \in \{0, 1\}$ is brand $i$’s dummy variable (1 on promotion, 0 not on promotion), and $D^t$ is the discount rate.

We define brand $i$’s transition probability of price promotion in condition $j \in \{0, 1\}$ at time $t$ as

$$q_{j1} = \Pr \{x_{i,t+1} = 1 | x_i^t = j\},$$

$$q_{j0} = \Pr \{x_{i,t+1} = 0 | x_i^t = j\} = 1 - q_{j1}. $$

(15)

Let $x_t = (x_1^t, x_2^t, \ldots, x_n^t)^T$ be the vector of price promotion, where $n$ is the number of brands. Then the transition probabilities of all brand’s price promotions are given by

$$q(x_t, x_{t+1}) = \prod_{i=1}^{n} q_{j_i}^{x_i^t, x_{i,t+1}} = q_1^{x_1^t, x_{1,t+1}} \times q_2^{x_2^t, x_{2,t+1}} \times \cdots \times q_n^{x_n^t, x_{n,t+1}}.$$
We define consumer $h$’s expected utility at $t$ as

$$V^h_t(x_t) = \mathbb{E} \left[ d^h_t (P^h_t(\text{inc}) \hat{W}^n_{1,t}(x_t)) + (1 - P^h_t(\text{inc})) \hat{W}^h_{0,t}(x_t)) + (1 - d^h_t)OV^h_t(x_t) \right], \quad (17)$$

where the dummy variable $d^h_t \in \{0, 1\}$ indicates whether consumer $h$ visits the store or not. If consumers visit the store, they decide to purchase or not, and then they obtain the utility of purchase or non-purchase. If consumers do not visit the store, they are considered to obtain the utility of their next purchase opportunity. In this case, the utility is the option value of postponing purchase.

Consumer $h$’s option value of postponing purchase $OV^h_t(x_t)$ at $t$ is calculated by expectation of expected utilities at $t+1$:

$$OV^h_t(x_t) = \sum_{x_{t+1}} q(x_t, x_{t+1}) V^h_{t+1}(x_{t+1}). \quad (18)$$

Note that the time preference rate is absorbed by parameter $\theta_{0,\tau}$ in Eq. (11). Figure 1 shows the calculation of the option value when $n = 2$. At time $T^h$, consumer $h$’s inventory of the product category is out from Eq. (2). Therefore, we assume the value of postponing purchase at $T^h$ as follows:

$$OV^h_{T^h}(x_{T^h}) = 0. \quad (19)$$

Starting from time $T^h$, we can calculate the option value at each time via backward induction.

---

1 In a real options approach, an option value is calculated as the expected present value discounted by the time preference rate. Then Eq. (18) should be modified by a time preference rate $\delta$:

$$\delta OV^h_t(x_t) = \delta \sum_{x_{t+1}} q(x_t, x_{t+1}) V^h_{t+1}(x_{t+1}). \quad (18')$$

In our model, however, deterministic utility of non-purchase $\hat{W}^h_{0,t}$ is estimated in the form of Eq. (11). If we use the option value in Eq. (18'), deterministic utility of non-purchase should have the form of

$$\hat{W}^h_{0,t} = \pi_0, \tau + \delta \theta_{0,\tau} \cdot OV^h_t.$$

Consequently, we have $\theta_{0,\tau} = \delta \theta_{0,\tau}$, which means that the time preference rate $\delta$ is absorbed by parameter $\theta_{0,\tau}$.
2.3 Parameter Estimation

We estimate the unknown parameters, \( u^i \) and \( \beta \) in the brand choice model, and \( \pi_{0,t}, \pi_{1,t}, \theta_{0,t} \) and \( \theta_{1,t} \) in the purchase incidence model, by the maximum likelihood method. Because we use a nested logit model, we estimate the parameters in the brand choice model first. The likelihood function of brand choice model \( L(\text{cho}) \) is given by

\[
L(\text{cho}) = \prod_i \prod_h \prod_t P^h_{t}(i|\text{inc})y_{h;i}^{t},
\]

where the dummy variable \( y_{h;i}^{t} \) indicates whether the consumer \( h \) chooses brand \( i \) at \( t \) or not.

Next we estimate the parameters in the purchase incidence model. We cannot estimate for entire period at once, because the option value of postponing purchase at time \( t \), \( OV_{h}^{t}(x_t) \), includes the value at time \( t + 1 \). Therefore, we separate the data into each estimated time until out of inventory \( \tau_{h}^{t} \), after which we can estimate from \( \tau_{h}^{t} = 0 \) to \( \tau_{h}^{T} = T^{h} \) via backward induction. The likelihood function of purchase incidence model \( L(\text{inc}) \) is given by

\[
L(\text{inc}) = \prod_h \prod_t P^{h}_{t}(\text{inc})y_{h}^{t},
\]

where the dummy variable \( y_{h}^{t} \) indicates whether the consumer \( h \) purchases or not at \( t \).

3 Data Analyses

3.1 Data

We validate our model by using POS data with ID of a supermarket at Kanagawa, provided by Nikkei Media Marketing. The data include all product categories, excluding fresh food, and the supermarket is located in an apartment area. The date covers one year, from 1 January 2001 to 31 December 2001, and covers each household’s purchase history. We consider household inventory, so our model is inappropriate if consumers purchase at other retail stores. However, the supermarket is the only big retail store in its area, and the supermarket gives reward points as an incentive to purchase at their shop. Therefore, the data well fit our model. We use ketchup purchase history for our validation, and we use only the data from 1 January 2001 to 30 September 2001, because there were no new ketchup products during this interval. For the households, we use only the data of the 144 households that purchased more than three times in the period because these households can be considered to consume ketchup often and to mainly purchase at the supermarket. In consideration of purchase opportunity number, we convert the data from daily to weekly. We choose the top three brands by share of sales, and all other brands are lumped together as “other brands”; the total share of the top three brands is 93.5%.

In our model, price has two states, the promotion price and the usual price, but for other brands, we ignore price promotion. Because other brands do not have frequent promotions and the discount percentage is fairly low, the effect on the estimation parameters is low, especially because of the low sales share. We standardize the category value \( CV \) and the option value to postpone purchase \( OV \) at each time until out of inventory, so that we can uniform the magnitude of parameter values. If scales are different, calculated parameter values include the scale effects, so we can not compare the
Table 1: Fitness in terms of log likelihood, AIC, and BIC on purchase incidence model.

| Model                  | Log Likelihood | AIC    | BIC    |
|------------------------|----------------|--------|--------|
| Bucklin and Gupta [5]  | -1633.3        | 3274.5 | 3300.7 |
| Our Model              | -1530.1        | 3124.1 | 3333.2 |

parameter values merely. As the result of standardization, we can treat expected values of stochastic
factors as $\varepsilon = 0$. The factors are defined as having the Gumbel distribution, and the expected values
affect only the scale of the utility. So, we can calculate the parameters under the condition $\varepsilon = 0$.
Furthermore, so as to decide the benchmark of the parameter scales, we treat deterministic utility
of other brands as 0 in brand choice model, as well as deterministic utility of non-purchase as 0 in
purchase incidence model.

3.2 Results

Bucklin and Gupta [5] constructed a model of purchase incidence and brand choice as a nested logit
model, but they did not consider the option value of postponing purchase. Therefore, we compared
our results with those of Bucklin and Gupta [5] in order to validate the superiority of considering the
option value of postponing purchase by log likelihood, AIC, and BIC.\footnote{AIC (Akaike’s Information Criterion) and BIC (Bayesian Information Criterion) are criteria to measure the fitness of statistical models. Both criteria have a penalty term for the number of parameters, while the penalty in BIC is larger than in AIC.} Bucklin and Gupta [5] has the
same brand choice model as ours, but a different purchase incidence model. The utility of purchase is
defined as

$$W_t^h = w + \alpha_1 CV_t^h + \alpha_2 INV_t^h + \alpha_3 CR_t^h,$$

(22)

where $w$ is the characteristic value of purchase, $CV_t^h$ is the category value, $INV_t^h$ is the household
inventory, and $CR_t^h$ is the average consumption rate.

Table 1 shows fitness of purchase incidence for our model and Bucklin and Gupta [5] in terms of log
likelihood, AIC, and BIC. Despite the number of parameters in our model being 32 and that in Bucklin
and Gupta [5] being 4, our model is better according to AIC and only slightly worse according to BIC.
This implies that our model also being superior in terms of log likelihood is not due to the number of
parameters. Bucklin and Gupta [5] consider the category value, household inventory, and average rate
of consumption as explanatory variables in the purchase incidence model. In our model, we calculate
the option value of postponing purchase from household inventory, average rate of consumption, and
uncertainty of the price. Thus, it is better to consider the uncertainty of the price in terms of model
fitness, which is what allowed us to demonstrate the superiority of considering the value of postponing
purchase by a real options approach.

Tables 2 and 3 show the results of parameter estimation of our model. In Table 2, the characteristic
value of brand 3 is negative. The value is estimated by the comparative validation based on the
characteristic value of other brands as 0. It means that brand 3 is less attractive than other brand.
However, in spite of the low characteristic value, brand 3 is included in the top 3 of share in the
category. This is because brand 3 is attractive product when it is on price promotion due to the
Table 2: Parameters of brand choice model.

|       | $u^i$ | $\beta^i$ |
|-------|-------|-----------|
| Brand 1 | 1.29  | 0.86      |
| Brand 2 | 1.36  | 0.60      |
| Brand 3 | -3.40 | 6.00      |
| Other Brands | 0.00 | —         |

Table 3: Parameters of purchase incidence model.

| $\tau^h_t$ | $\pi_{1,\tau_t}$ | $\theta_{1,\tau_t}$ | $\pi_{0,\tau_t}$ | $\theta_{0,\tau_t}$ |
|------------|------------------|---------------------|------------------|---------------------|
| 0          | -1.19            | 0.12                | 0.00             | —                   |
| 1          | 0.24             | -0.03               | 0.00             | -0.60              |
| 2          | -1.86            | 0.45                | 0.00             | -0.55              |
| 3          | -2.18            | 0.77                | 0.00             | 0.41               |
| 4          | -2.33            | 0.24                | 0.00             | -0.03              |
| 5          | -2.22            | 0.25                | 0.00             | -0.05              |
| 6          | -2.17            | 0.10                | 0.00             | -0.29              |
| 7          | -2.50            | 0.95                | 0.00             | -0.61              |
| 8          | -2.58            | 0.47                | 0.00             | -0.22              |
| 9          | -2.60            | 0.13                | 0.00             | 0.04               |
| 10         | -3.13            | 0.25                | 0.00             | 0.04               |

much higher value of $\beta^3$ than other brand. Note in particular that in Table 3 there is no trend in the parameter values of $\theta_{0,\tau_t}$ over time. One possible explanation is that consumers do not consume ketchup every day.

Table 3 is the calculated parameters of our purchase incidence model. The characteristic value of purchase $\pi_{1,\tau_t}$ is positive at $\tau^h_t = 1$. It means that consumers tend to purchase until out of inventory. However, $\pi_{1,\tau_t}$ is negative at $\tau^h_t = 0$. So, some consumers don’t purchase even upon out of inventory. The data we use is ketchup that is considered not to be consumed every day, so consumers purchase it as necessary. However, the longer $\tau^h_t$ is, the smaller $\pi_{1,\tau_t}$ is. Therefore, it turns out that consumers purchase with considering the out of inventory. Next, we can not see any trend in the parameters of $CV$ and $OV$. This is because we calculated the parameters from $\tau^h_t = 0$ to $\tau^h_t = T^h$ via backward induction, then the effects of $CV$ and $OV$ include the characteristic value $\pi_{1,\tau_t}$. So, it is required to build another method to calculate parameters so as to extract the trend and reduce the number of parameters.

Table 4 shows the result of parameters in purchase incidence model of Bucklin and Gupta [5]. The calculated weight of $CV$ is higher than others, which means that $CV$ has a strong effect to consumer behavior. Comparing Table 3 with Table 4, the relative magnitude relation between the characteristic

Table 4: Parameters of purchase incidence model (Bucklin and Gupta [5]).

| $w$  | $\alpha_1$ | $\alpha_2$ | $\alpha_3$ |
|------|------------|------------|------------|
| -1.79| 0.30       | -0.02      | 0.09       |
values of purchase ($\pi_{1,t}$ in Table 3 and $w$ in Table 4) and the calculated parameters of $CV$ ($\theta_{1,t}$ in Table 3 and $\alpha_1$ in Table 4) is almost same. It turns out that the effect of $CV$ still remains even though $OV$ is included in our model. And in Table 3, the calculated parameters of $CV$, $\theta_{1,t}$, and $OV$, $\theta_{0,t}$, are also at almost same level. Because we standardize $OV$ and $CV$, $OV$’s effect to consumer behavior is as much as $CV$’s. Together with the results of likelihood, AIC and BIC in Table 1, these discussion show our model has superiority over Bucklin and Gupta [5].

4 Conclusion

It has previously been shown that price promotion by retail stores strongly affects consumer purchase behavior and that consumers tend to purchase at a lower price and postpone purchase at a higher price. Several studies have considered such consumer purchase behavior, but the parameter estimation of these models is highly complex. For this study, we constructed a model of purchase incidence and brand choice under price uncertainty by using a real options approach, which is an approach typically applied in investment decisions. Here, we have applied this approach to consumer purchase behavior in order to calculate the option value of postponing purchase. The proposed model considers price uncertainty in a nested logit model, which makes parameter estimation easier than in the dynamic structure model case.

From the results for real purchase historical data, we have validated our model’s superiority, which is attributable to it taking into account the option value of postponing purchase. This result demonstrates the improved model fitness that can be obtained by combining a consumer purchase behavior model and a real options approach to consider price uncertainty. Many retail stores collect purchase historical data and individual attribution data by a POS system and smartphone apps and then try to use the data for sales promotions. One way to use these data is to target promotions to individual customers, in particular in terms of the timing and discount rate for each customer, for which the proposed model is particularly useful.

Future work includes the following. First, decreasing the number of parameters. We have estimated the parameters backward from the out-of-inventory time, so the number of the parameters in our model is much higher than those in previous studies. Even though we have shown the superiority of our model, we should try to decrease the number of parameters in order to further improve it.

Secondly, validation for other stockable product categories. As shown in Table 3, no trend over time of parameter values was observed in the results using ketchup data. It might be that consumers do not consume ketchup every day, and therefore the time effect on parameter values is only slight. Therefore, the model should also be validated with data of other stockable product categories.

Thirdly, applying a real options approach for non-stockable product categories. For non-stockable product categories, consumers tend to purchase many different brands, since they easily become bored with a particular brand if it is purchased repeatedly. This is called variety-seeking behavior and many previous studies on it have been conducted. Therefore, we should apply a real options approach to non-stockable product categories in consideration of this variety-seeking behavior.
A Model of Purchase Behavior under Price Uncertainty: A Real Options Approach

Acknowledgment

The authors would like to thank the editor Ryuta Takashima and two anonymous referees for their valuable comments.

References

[1] Bell, D. R. and Bucklin, R. E. (1999): The role of internal reference points in the category purchase decision, *Journal of Marketing Research*, **26**, 128–143.

[2] Ben-Akiva, M. and Lerman, S. R. (1985): *Discrete choice analysis*, MIT Press, Cambridge.

[3] Boyd, D. E. and Brown, B. P. (2012): Marketing control rights and their distribution within technology licensing agreements: a real options perspective, *Journal of Academy of Marketing Science*, **40**, 659–672.

[4] Bucklin, R. E. and Lattin, J. M. (1991): A two-state model of purchase incidence and brand choice, *Marketing Science*, **10**, 24–39.

[5] Bucklin, R. E. and Gupta, S. (1992): Brand choice, purchase incidence, and segmentation: An integrated modeling approach, *Journal of Marketing Research*, **26**, 201–215.

[6] Chintagunta, P. K. and Haldar, S. (1998): Investigating purchase timing behavior in two related product categories, *Journal of Marketing Research*, **35**, 43–53.

[7] Erdem, T. Imai, S. and Keane, M. P. (2003): Brand and quantity choice dynamics under price uncertainty, *Quantitative Marketing and Economics*, **1**, 5–64.

[8] Gudagni, P. M. and Little, D. C. (1983): When and what to buy: a nested logit model of coffee purchase, Working Paper, 1919-1987, Sloan School of Management, MIT.

[9] Gupta, S. (1988): Impact of sales promotion on when, what, and how much to buy, *Journal of Marketing Research*, **25**, 342–355.

[10] Gupta, S. (1991): Stochastic models of interpurchase time with time-dependent covariates, *Journal of Marketing Research*, **28**, 1–15.

[11] Haenlein, M., Kaplan, A. M., and Schoder, D. (2006): Valuing the real option of abandoning unprofitable customers when calculating customer lifetime value, *Journal of Marketing*, **70**, 5–20.

[12] Jiang, M. S., Aulakh, P. S., and Pan, Y. (2009): Licensing duration in foreign markets: a real options perspective, *Journal of International Business Studies*, **40**, 559–577.

[13] Lattin, J. M. and Bucklin, R. E. (1989): Reference effect of price and promotion on brand choice behavior, *Journal of Marketing Research*, **26**, 299–310.

[14] Manchanda, P., Ansari, A. and Gupta, S. (1999): The shopping basket: A model for multicategory purchase incidence decisions, *Marketing Science*, **18**, 95–114.
[15] Rajendran, K. N. and Tellis, G. J. (1994): Contextual and temporal components of reference price, *Journal of Marketing Research*, **58**, 22–34.

[16] Siddhartha, C., Seetharaman, P. B. and Strijnev, A. (2004): Model of brand choice with a no-purchase option calibrated to scanner-panel data, *Journal of Marketing Research*, **41**, 184–196.

[17] Sun, B., Neslin, S. A. and Srinivasan, K. (2003): Measuring the impact of promotion on brand switching when consumers are forward looking, *Journal of Marketing Research*, **40**, 389–405.

[18] Ziedonis, A. A. (2007): Real options in technology licensing, *Management Science*, **53**, 1618–1633.