Price Customization Using Price Thresholds Estimated From Scanner Panel Data

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Abstract

This study explores a customized pricing strategy based on heterogeneous price thresholds estimated from scanner panel data to show that customized pricing could be more efficient than a flat pricing strategy. A heterogeneous brand choice model with price thresholds is applied to price customization problem and we demonstrate that heterogeneous price thresholds are valuable information set for the search of efficient pricing levels customized to individual consumers. The expected incremental profits from customized discounting as well as customized price hike are evaluated by using hierarchical Bayes modeling with Markov chain Monte Carlo (MCMC) method.

Key Words and Phrases
Price Threshold, Latitude of Price Acceptance, Brand Choice, Bayesian MCMC, Heterogeneity, Scanner Panel Data, Customized Pricing

1. Introduction

Not only marketers but also marketing researchers have recognized that customizing marketing activities would be valuable to improving the profitability of direct marketing efforts. Electronic distributions of coupons through frequent shopper programs and their collected household's purchase record have made its potential advantage more realistic in the marketplace.

Price customization or the first degree price discrimination was discussed as target couponing by Rossi, McCulloch and Allenby (1996). They measure the value of heterogeneous household information by evaluating incremental profits generated from sales increase by issuing different level of discount coupon to show that there exists a potential for improving the profitability of direct marketing efforts by fully utilizing household purchase histories. Their modeling is now established as a benchmark model for consumer marketing to conduct target marketing.

Terui and Dahana (2004) proposed a choice model with the heterogeneous price thresholds, which extends conventional heterogeneous choice model with linear utility function to that with nonlinear utility function. Besides the price thresholds, the model incorporates the concepts of symmetric market response and reference price discussed in the literature of nonlinear market response of consumer behavior.

This heterogeneous price threshold model can be used for the search of efficient customized pricing. That is, the heterogeneous price thresholds provide the marketer with the price insensitive region of each consumer. The discount pricing not crossing over lower threshold leads to the loss because consumers do not respond to this discounting. On the contrary, in case of price hike, they do not recognize it as far as the price stays below upper price threshold and the differences from their reference prices produce the profits to retailer. In other words, the heterogeneous price thresholds contribute toward minimizing the loss incurred from discount pricing over their lower price thresholds as well as maximizing the gain obtained from price hike below their upper price thresholds.

In this study, on the basis of heterogeneous price thresholds, we explore the profitability of customized pricing by considering not only different levels of discounting but also price hike strategy. We set various levels of pricing for each consumer to evaluate expected incremental sales and profits in the market by heterogeneous price thresholds estimated from scanner panel data. We show, under a limited simulation study, that optimal levels could occur near price thresholds and that a customization strategy on pricing could provide marketers with larger profits than a "non-customized (flat)" pricing strategy.

The organization of the paper is as follows. In section 2, we describe heterogeneous price threshold model and define incremental sales and profits generated by customized pricing. We take up not only discounting but also price hike for customization strategy. Section 3 presents the application of scanner panel data to our model. We use instant coffee category panel data because of availability and we intend to see how our methodology is applicable to scanner panel data. Section 4 concludes this paper. The appendix explains details of the evaluation of incremental profits including the algorithm for hierarchical Bayes modeling via Markov chain Monte Carlo method.

2. Heterogeneous Price Threshold Model and Customized Pricing

There have been many studies for the price thresholds and the latitude of price acceptance. Related recent studies include Gupta and Cooper (1992), Kalwani and Yim (1992), Kalyanaram and Little (1994), and Han, Gupta and Lehman (2001). However, these previous models with threshold effects yielding intervals of price acceptance have yet to be estimated heterogeneously.

On the other hand, Terui and Dahana (2004) introduced a three-regime piecewise-linear stochastic utility function with two price thresholds and proposed a class of brand choice model – heterogeneous price threshold model – under a framework of a continuous mixture modeling for heterogeneous consumers. This choice model is characterized as a piecewise linear form so that consumers switch their utility structure according as determined by the relationship between the sticker shock, i.e., the difference between retail price and the reference price, and the price thresholds. Price thresholds generate unconventional discontinuous likelihood function in the analysis and they create difficulties in estimation. However, the method directly models thresholds for choice model in a general manner and coherent statistical inference on the thresholds can be done particularly when the number of samples is scarce.

Following empirical application by using scanner data of instant coffee market, our proposed three-regime heterogeneous reference-price probit model with thresholds was shown to be superior to other candidate models in the sense of marginal likelihood criterion. The comparable models included aggregate (homogeneous) reference price probit model without a threshold (Winer (1986), Putler (1992) and Mayhew and Winer (1992)); two regimes heterogeneous reference price probit model without a threshold (Bell and Lattin (2000), and Chang, Siddarth and Weinberg (1999)). This result was robust relative to the selection of the types of reference price.

Furthermore, our result added to the literature on the presence of reference prices and loss aversion that initially began with effects uncovered in scanner data, for example, as indicated by Winer (1986), Putler (1992), and Mayhew and Winer (1992), and then Chang, Siddarth and Weinberg (1999) and Bell and Lattin (2000) showed that reference prices' effects disappear when heterogeneity was incorporated. It also showed that the reference effect and loss aversion return, at least for the data used in this study, after price thresholds are taken into a heterogeneous model. The degree of loss aversion is attenuated relative to results obtained using the homogeneity model without price thresholds.

Heterogeneous Price Threshold Model

We first define heterogeneous price threshold model proposed by Terui and Dahana (2004). To specify the utility function used in the model, we assume that consumer h's utility to brand j at time t of purchase, U_{jht}, reflects a linear function of k kinds of explanatory variables. We also suppose that consumer h has a reference price RP_{jht} for brand j, and that two price thresholds r_{1h} and r_{2h} ($r_{1h} < 0 < r_{2h}$). Consequently, we define the three regimes – gain "(g)", price acceptance "(a)", loss "(l)" – utility function to brand j as

$$U_{jht} = \begin{cases} u_{jh}^{(g)} + X_{jht}^{(g)} b_h^{*(g)} + \in_{jht}^{(g)} & \text{if } P_{jht} - RP_{jht} \le r_{1h} \\ u_{jh}^{(a)} + X_{jht}^{(a)} b_h^{*(a)} + \in_{jht}^{(a)} & \text{if } r_{1h} < P_{jht} - RP_{jht} \le r_{2h}, \\ u_{jh}^{(l)} + X_{jht}^{(l)} b_h^{*(l)} + \in_{jht}^{(l)} & \text{if } r_{2h} < P_{jht} - RP_{jht}, \end{cases} \tag{1}$$

where $X_{jht}^{(i)}$ is the row vector of explanatory variables (price, display, feature and brand royalty) allocated to regime "i" according to the level of sticker shock $P_{jht} - RP_{jht}$ (P_{jht}: the retail price exposed to consumer h) at the occasion, $b_h^{*(i)}, i = g, a, l,$ represent different market responses around the reference price. Finally, $\in_{jht}^{(i)}, i = g, a, l,$ respectively represent stochastic error components in the utility for each regime. We assume that they are independent across regimes. The meaning of this stochastic utility function is described in figure 1.

Figure 1: Price Threshold Model and Market Response

From that definition, the latitude of price acceptance (LPA hereafter) for consumer h under the conditions discussed below can be expressed as $L_h = (r_{1h}, r_{2h}]$. In order for the second regime of the utility function (1) to be characterized as the LPA and for r_{1h} and r_{2h} to be interpreted as price thresholds literally, i.e., for our proposed model to be recognized as a price threshold model, we impose the restriction of insensitiveness on the price-response parameter in the LPA regime as $b_{hp}^{(a)} \sim N(0, s_{hp}^{(a)2})$, which is an element of $b_h^{*(a)}$.

Following the utility function defined as (1), consumer h's probability of choosing brand j is written as

$$\Pr\{c_h = j\} = \begin{cases} \Pr\{y_{jh}^{(g)} = \max(y_{1h}^{(g)},\ldots,y_{m-1h}^{(g)}) > 0\} & \text{if } P_{jht} - RP_{jht} < r_{1h} \\ \Pr\{y_{jh}^{(a)} = \max(y_{1h}^{(a)},\ldots,y_{m-1h}^{(a)}) > 0 \mid R\} & \text{if } r_{1h} \le P_{jht} - RP_{jht} \le r_{2h} \\ \Pr\{y_{jh}^{(l)} = \max(y_{1h}^{(l)},\ldots,y_{m-1h}^{(l)}) > 0\} & \text{if } P_{jht} - RP_{jht} \ge r_{2h}, \end{cases} \qquad (2)$$

where $y_{jht} = U_{jht} - U_{mht}$ represents the relative utility from the last brand and $\Pr\{y_{jh}^{(a)} = \max(y_{1h}^{(a)},\ldots,y_{m-1h}^{(a)}) > 0 \mid R\}$ indicates the choice probability under the restriction on price response $b_{hp}^{(a)} \sim N(0, s_{hp}^{(a)2})$ in the LPA regime. Consumers' heterogeneity is incorporated through random effect specification that allows determination of the relationship between the price thresholds and consumer characteristics.

$$r_{1h} = Z_h^r f_1 + h_{1h}; \quad r_{2h} = Z_h^r f_2 + h_{2h}; \; h = 1,\cdots,H,$$

where Z_h^r is a vector of d kinds of household specific variables. We assume that $r_{1h} < 0 < r_{2h}$ for identification and $h_{jh} \sim N(0, s_{jh}^2)$ for $j = 1,2$. We also set a hierarchical structure of "between subjects model for regime i" for the market response parameter

$$b_h^{(i)} = \Delta^{(i)} Z_h^b + u_h^{(i)}; \quad u_h^{(i)} \overset{\text{i.i.d}}{\sim} \mathrm{N}\left(0, V_b^{(i)}\right), \quad h = 1,\cdots,\mathrm{H}., \; i = g,a,l,$$

where Z_h^b contains another vector of d' kinds of household specific variables. In particular, we note that price response $b_{hp}^{(a)}$ in the LPA is assumed *a priori* to have zero mean.

As for model calibration, we employ hierarchical Bayes modeling to implement the threshold probit model (2). Our model includes a threshold variable in the model and it induces discontinuities in the likelihood relative to thresholds. In general, the proposed model is difficult to estimate with conventional methods because the likelihood is not differentiable in r_h. Conventional maximum likelihood estimation collapses and classical asymptotic distribution theory is not operative on this parameter. However, we can apply Metropolis-Hasting sampling algorithm for price thresholds to obtain conditional posterior "$r_h \mid \{I_{ht}\},\{X_{ht}\},\{b_h^{(i)}\},\Lambda^{(i)},\{z_h\},f,\Sigma_h$". Prior distributions and MCMC estimation procedures for these hierarchical Bayes models are described in Terui and Dahana(2004). Brief summary of model estimation algorithm focusing on incremental sales and profit is described in the appendix.

Next we consider price customization strategy by using this price threshold model.

Incremental Sales and Profits by Customized Pricing Strategy

Based on the knowledge of heterogeneous price thresholds for respective consumer obtained by proposed model, we consider customized pricing, both of discounting and price hike, and explore a possible efficient pricing.

[1] Discounting

Conditional on the draw of $\left\{\left(r_{1h}(<0), b_h^{(1)}, b_h^{(2)}\right), h=1,...,H\right\}$, we set discounting level of $\left(r_{1h}+a\right)$ (>0), ($a=0,\pm1,...,\pm15\%$) for $h=1,...,H$, and we define the expected incremental sales, $IS_j^{(-)}(a \mid \{r_{1h}, b_h, h=1,...,H\})$, for "customized discounting" averaged over households as

$$IS_j^{(-)}(a \mid \{(r_{1h}, b_h^{(1)}, b_h^{(2)}), h=1,...,H\}) = \begin{cases} \frac{1}{H}\sum_{h=1}^{H}\left[\Pr_j\left(b_h^{(1)}, P_{jh0}\left(1-\left(r_{1h}+a\right)\right)\right)-\Pr_j\left(b_h^{(2)}, P_{jh0}\right)\right] \text{ if } a \ge 0 \text{: (Price Gain)} \\ \frac{1}{H}\sum_{h=1}^{H}\left[\Pr_j\left(b_h^{(2)}, P_{jh0}\left(1-\left(r_{1h}+a\right)\right)\right)-\Pr_j\left(b_h^{(2)}, P_{jh0}\right)\right] \text{ if } a < 0 \text{: (LPA)} \end{cases} \quad (3)$$

Under the assumption of margin M %, the corresponding incremental profit is defined as

$$IP^{(-)}{}_j(a \mid \{(r_{1h}, b_h^{(1)}, b_h^{(2)}), h=1,...,H\}) = \begin{cases} \frac{1}{H}\sum_{h=1}^{H}\left[\Pr_j\left(b_h^{(1)}, P_{jh0}\left(1-\left(r_{1h}+a\right)\right)\right)-\Pr_j\left(b_h^{(2)}, P_{jh0}\right)\right]\left(M-\left(r_{1h}+a\right)\right) \text{ if } a \ge 0 \text{: (Price Gain)} \\ \frac{1}{H}\sum_{h=1}^{H}\left[\Pr_j\left(b_h^{(2)}, P_{jh0}\left(1-\left(r_{1h}+a\right)\right)\right)-\Pr_j\left(b_h^{(2)}, P_{jh0}\right)\right]\left(M-\left(r_{1h}+a\right)\right) \text{ if } a < 0 \text{: (LPA)} \end{cases} \quad (4)$$

Taking expectation of (10) and (11) with respect to posterior distribution of $\left(r_{1h}, b_h^{(1)}, b_h^{(2)}\right)$ leads to unconditional incremental sales and profits resectively,

$$IS^{(-)}{}_j(a) = E_{(r_{1h}, b_h^{(1)}, b_h^{(2)})}\left[IS^{(-)}{}_j(a \mid \{r_{1h}, b_h^{(1)}, b_h^{(2)}, h=1,...,H\})\right] \quad (5)$$

$$IP^{(-)}{}_j(a) = E_{(r_{1h}, b_h^{(1)}, b_h^{(2)})}\left[IP^{(-)}{}_j(a \mid \{r_{1h}, b_h^{(1)}, b_h^{(2)}, h=1,...,H\})\right]. \quad (6)$$

These estimates are obtained as by-product of sampling through MCMC iterations.

[2] Price hike

As for price hike strategy, conditional on $\left\{\left(r_{2h}(>0), b_h^{(2)}, b_h^{(3)}\right), h=1,...,H\right\}$, we set the hike rate $(r_{2h}+a)$ % (> 0) for $h=1,...,H$ ($a = 0, \pm 1, ..., \pm 15\%$), then the expected incremental sales and profits for "customized price hike strategy" averaged over households are respectively defined as

$$IS_j^{(+)}(a \mid \{(r_{2h}, b_h^{(2)}, b_h^{(3)}), h=1,...,H\}) = \begin{cases} \frac{1}{H}\sum_{h=1}^{H}\left[\Pr_j\left(b_h^{(2)}, P_{jh0}\left(1+\left(r_{2h}+a\right)\right)\right)-\Pr_j\left(b_h^{(2)}, P_{jh0}\right)\right] \text{ if } a < 0 \text{: (LPA)} \\ \frac{1}{H}\sum_{h=1}^{H}\left[\Pr_j\left(b_h^{(3)}, P_{jh0}\left(1+\left(r_{2h}+a\right)\right)\right)-\Pr_j\left(b_h^{(2)}, P_{jh0}\right)\right] \text{ if } a \ge 0 \text{: (Price Loss)} \end{cases} \quad (7)$$

$$IP^{(+)}{}_j(a \mid \{(r_{2h}, b_h^{(2)}, b_h^{(3)}), h=1,...,H\}) = \begin{cases} \frac{1}{H}\sum_{h=1}^{H}\left[\Pr_j\left(b_h^{(2)}, P_{jh0}\left(1-\left(r_{2h}+a\right)\right)\right)-\Pr_j\left(b_h^{(2)}, P_{jh0}\right)\right]\left(M-\left(r_{2h}+a\right)\right) \text{ if } a < 0 \text{: (LPA)} \\ \frac{1}{H}\sum_{h=1}^{H}\left[\Pr_j\left(b_h^{(3)}, P_{jh0}\left(1-\left(r_{2h}+a\right)\right)\right)-\Pr_j\left(b_h^{(2)}, P_{jh0}\right)\right]\left(M-\left(r_{2h}+a\right)\right) \text{ if } a \ge 0 \text{: (Price Gain)} \end{cases} \quad (8)$$

The unconditional expected incremental sales and profits are respectively described as

$$IS^{(+)}{}_j(a) = E_{(r_{2h}, b_h^{(2)}, b_h^{(3)})}\left[IS^{(+)}{}_j(a \mid \{r_{2h}, b_h^{(2)}, b_h^{(3)}, h=1,...,H\})\right] \quad (9)$$

$$IP^{(+)}{}_j(a) = E_{(r_{1h}, b_h^{(2)}, b_h^{(3)})}\left[IP^{(+)}{}_j(a \mid \{r_{2h}, b_h^{(2)}, b_h^{(3)}, h=1,\dots,H\})\right]. \tag{10}$$

[3]Difference from non-customized pricing

The average difference of incremental profits between an optimal customized discounting at the level r_{1h} and a non-customized (flat) discounting at the level d^* can be denoted by

$$\begin{aligned} &DIF_j^{(-)}(d^* \mid \{r_{1h}, b_h^{(\cdot)}, h=1,\dots,H\}) \\ &= \tfrac{1}{H}\sum_{h=1}^{H}\left(\Pr_j\left(b_h^{(1)}, P_{j0}(1-r_{1h})\right) - \Pr_j\left(b_h^{(2)}, P_{j0}\right)\right)(M - r_{1h}) \\ &\qquad - \tfrac{1}{H}\sum_{h=1}^{H}\left(\Pr_j\left(b_h^{(\cdot)}, P_{j0}(1-d^*)\right) - \Pr_j\left(b_h^{(2)}, P_{j0}\right)\right)(M - d^*) \end{aligned} \tag{11}$$

where market response $b_h^{(\cdot)}$ for non-customized pricing depends on the regime determined by discount level d^*. Unconditional estimate is obtained by taking expectation

$$DIF_j^{(-)}(d^*) = E_{(r_{1h}, b_h^{(\cdot)})}\left[DIF_j^{(-)}(d^* \mid \{r_{1h}, b_h^{(\cdot)}, h=1,\dots,H\})\right]. \tag{12}$$

The same operation is applied to price hike strategy at an optimal customized price hike at the level r_{2h} compared with non-customized discounting at the level d^* to obtain

$$DIF_j^{(+)}(d^*) = E_{(r_{2h}\ b_h^{(\cdot)})}\left[DIF_j^{(+)}(d^* \mid \{r_{2h}, b_h^{(\cdot)}, h=1,\dots,H\})\right]. \tag{13}$$

We note that the marketer taking non-customized pricing strategy does not know the price thresholds and therefore he/she has to try constant pricing to every consumer at possible levels. We also note that the assumption of constant margin (*M* %) imply that the price discounts are optimized and this is consistent with some other papers in the area, for example, Kopalle, Mela, and Marsh (1999).

3. Empirical Application to Scanner Panel Data

3-1. Data, Variables and Model Specification

Video Research Ltd., Japan, supplied scanner panel data for the instant coffee (regular) category. In all, 2,840 records for 197 panels during 1990–1992 were available. We assume that five national brands existed in the market during the tracking period. There are 11 brands in the data set and we deal with five primary brands A, B, C, D, and E, which totally account for 75.6% market share.

Table 1 provides descriptive information about the data. Brand B has the maximum share – over 48.03%; the minimum share – approximately 5.74% – is for brand E. We rescale all prices as yen/100 g to equalize quantitative differences for each package of the five brands. The aggregated price in table 1 was calculated by averaging the prices normalized by 100 gm over the whole purchase occasions in the data. We found that the price correlations between different volumes of SKU's are positively higher (0.794 max, 0.740 min).

Table 1 Descriptive Statistics for Data

Variables for our model are:

• Explanatory Variables: X = [Constant, Price, Display, Feature, GL],

where Price is the log(price); Display and Feature are binary values; and GL is state dependent variable defined as a smoothing variable over past purchases proposed by Guadagni and Little (1983) as $GL_{jht} = a\, GL_{jht} + (1-a) I_{j\,h,t-1}$, where a grid search (Keane(1997)) is applied to fix the smoothing parameter as 0.75 based on the criterion of minimum marginal likelihood.

• Household Specific Variables: Z^r = [Constant, Dprone, Pfreq, *RP*, *BL*],

where Dprone is the deal proneness defined as the proportion of purchase (of any the five brands) made on promotion (Bucklin and Gupta (1992), Han et al. (2001))); Pfreq is the shopping frequency (three categories); *RP* represents the measure of average reference price level as defined by $RP_h = \sum_{j=1}^{m} (\sum_{t=1}^{T_h} \log(RP_{jht}) / T_h) / m$ and *BL* represents the brand loyalty measure defined as $BL_h = \max_j (\sum_{t=1}^{T_h} GL_{jht} / T_h)$. These are used in Kalyanaram and Little (1994) and Han et al. (2001).

• Household Specific Variables: Z^b = [Constant, Hsize, Expend],

where Hsize is 1–6 (number of household members) and Expend is nine categories (shopping expenditure / month) used in Rossi et al. (1996).

As for the choice of reference price, Terui and Dahana (2004) employed four kinds of reference prices of two categories. That is, (A) $RP_{jht} = P_{jh,t-1}$, the price at its last purchase

(B) $RP_{jht} = a\,RP_{jh,t-1} + (1-a)P_{jh,t-1}$, the smoothed price over previous purchases;

(C) $RP_{jht} = P_{kht}$, where k means the brand at the last purchase and (D) $RP_{jht} = P_{rht}$, where r indicates the price of a brand chosen randomly at the time of purchase. As model specification, they showed that the marginal likelihood for each model suggests the model (C): stimulus-based *RP* (C)-3 regimes heterogeneous probit with thresholds and we use it as the estimated model for customized pricing in this paper.

3-2. Customized Pricing

Heterogeneous Distribution of Price Thresholds

Figure 2 shows the frequency distribution of Bayes estimates $\{\hat{r}_{1h}, h = 1,..., H\}$ and $\{\hat{r}_{2h}, h = 1,..., H\}$, where $\hat{r}_{\bullet h}$ is the mean of posterior distribution of threshold parameters for household h. Both distributions exhibit skewness showing distinct features each other. The average distances from zero are different: -0.113 for the lower threshold $\hat{r}_{1h}$ and 0.138 for the upper threshold $\hat{r}_{2h}$. For that reason, the symmetric LPA around zero could fail to reflect heterogeneity in the brand choice study.

Figure 2: Heterogeneous Distribution of Price Thresholds

We utilize the magnitude of price thresholds and their uncertainty expressed by distribution in figure 2 to explore the profitability of price customization effort in what follows.

Customized Discounting and Price hike

The price thresholds say that the discount pricing below lower threshold does not effect on sales because of non-response to this discounting. However, in case of price hike, consumer does not take a negative attitude as far as the price stays below upper price threshold and the differences from their reference prices produce the profits to retailer. Since the heterogeneous price thresholds contribute toward minimizing the loss incurred from discount pricing over their lower price thresholds as well as maximizing the gain obtained from price hike below their upper price thresholds, we expect that the price customization accommodating heterogeneous insensitive region makes it possible to identify an efficient pricing.

In order to evaluate the efficiency of price customization, we consider several levels of pricing for each consumer to evaluate expected incremental sales and profits in the market by using the knowledge obtained by heterogeneous price thresholds estimated from scanner panel data. We set the discounting level of $(r_{1h} + a)$ (>0)and the hike rate $(r_{2h} + a)$% (> 0) for $h = 1,...,H$, where $a = 0, \pm 1,..., \pm 15\%$.

Figure 3: Expected Incremental Sales

Figure 4: Expected Incremental Profits

The negative part each graph in figure 3 shows calculated expected incremental sales for the case of customized discounting. We observe that the large difference at the boundary r_{1h} between price gain and LPA regimes and the largest change happens for brand E having highest price, and for brand D with second highest price. Similarly, the negative part of figure 4 shows those expected incremental profits, where the margin was set as M =30%. We have an optimal discount level at the lower threshold r_{1h} for every brand, as we could expect. The positive region of each graph in figures 3 and 4 respectively shows expected incremental sales and profits for the case of customized price hike. We observe that maximum profit happens at the upper threshold r_{2h} for every brand.

Figure 5: Difference of Profit Between Customized and Non-customized Pricing

Next we compare the performance of customized pricing with that of flat pricing. We note that marketer taking a non-customized pricing strategy is oblivious to respective consumers' price thresholds, and thus marketer applies flat (constant) pricing to every consumer. The negative and positive regions of each graph of figure 5 respectively show the plots of $DIF_j^{(-)}(d^*)$ and $DIF_j^{(+)}(d^*)$ for $d^* = 1,2,...,15\%$. Different margins produce slightly different graph shapes, but the findings described below do not change.

First, this graph shows that two kinds of optimal customized pricing – discount at r_{1h} and hike at r_{2h} – dominate every level of non-customized pricing $d^* = 1,2,...,15\%$. In the negative LPA region, non-customized pricing does not generate so large sales increase as expected because of price change insensitivity over this region. In contrast, customized pricing does not take a discount strategy over this region. Identical logic applies to the case of price hike as shown in the positive part of LPA. Those gains for customized pricing stem from price threshold information. In the price gain regime as well as in the price loss regime, it would be reasonable to consider that efficiency can occur at those limits. Almost identical situations apply to other brands, but the change is largest for the highest-price brand E.

4. Concluding Remarks

In this study, we applied price thresholds model by Terui and Dahana (2004) to the exploration of customized pricing strategy by using scanner panel data.

We demonstrated that optimal customized pricing levels are provided at the lower price thresholds for discounting, and at the upper price thresholds for a price hike. Moreover, our performance-comparison exercises with possible non-customized pricing strategies showed that customized pricing could yield greater profits than flat pricing. These results are limited to our simulation study under specified conditions, although it would be plausible.

We used instant coffee category panel data because of availability and this could not be always appropriate data set for the price hike strategy. However our purpose of this application was to see how our methodology was applicable to panel data and we showed the possibility of application to other panel data set where customized price hike could be appropriate.

In the literatures of optimal pricing, for example, Greenleaf (1995), Kopalle, Rao, and Assuncao (1996) and Kopalle and Winer (1996) examine optimal pricing policies which are not customized to each individual but are allowed to vary over time, i.e. heterogeneity in the time horizon. On the other hand, our model incorporates only cross sectional heterogeneity in the analysis. The temporary discounting could lead to consumer stockpiling and it affects negatively to the purchase in the future. By contrary, temporary price hike could make restrained purchasing to hold it out to next purchase. However, we expect that customized pricing by using heterogeneous price thresholds keeps these reactions as small as possible, because it utilizes the limits of the range in which consumer does not recognize the price change. We also note that the reference price (RP) by itself could be affected by pricing strategy. The frequent price promotions can make consumer with memory based RP lower their level of RP, on the other hand, they might not affect the consumers with stimulus based RP. To incorporate the effect of pricing on RP into the analysis, we need to model heterogeneous consumer with several types of RP formation discussed by, for example, Mazumdar and Papatla (2000).

Full discussion regarding these dynamic effects, in addition to the papers above, including recent related work by Van Heerde et al. (2004) and others which explores factor decomposition of price promotion and its long term effects, is left for future investigation.

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Appendix

Markov chain Monte Carlo Algorithm for Incremental Sales and Profit

-Hierarchical Bayes Modeling of Threshold Probit Model-

Estimation of the Model

As for model calibration, we employ hierarchical Bayes modeling to implement the threshold Probit model (2). Given the value of r_h, according to the level of consumer h's sticker shock $P_{jht} - RP_{jht}$, we first assign data $\{X_{ht}\}$ of the explanatory variable to make $\{X_{jht}^{(i)}, i = g, a, l\}$ at each purchase occasion. The corresponding latent utility vector $\{y_{ht}^{(i)}, i = g, a, l\}$ is generated based on personal choice data $\{I_{ht}\}$ (the index of observed choices) using the algorithm of the Bayesian Probit model (Rossi et al. (1996, pp.338-339)) applied to each regime. Then, except for price threshold "$r_h \mid -$", we can use conditional posterior distributions: "$y_{ht}^{(i)} \mid \{I_{ht}\}, \{X_{ht}\}, b_h^{(i)}, \Lambda^{(i)}, r_h$", "$b_h^{(i)} \mid \{y_{ht}^{(i)}\}, \{X_{ht}^{(i)}\}, \Lambda^{(i)}, \Delta^{(i)}, V_b^{(i)}, z_h, r_h$", "$\Lambda^{(i)^{-1}} \mid \{y_{ht}^{(i)}\}, \{X_{ht}^{(i)}\}, \{b_h^{(i)}\}, \{r_h\}$", "$\Delta^{(i)} \mid \{b_h^{(i)}\}, V_b^{(i)}, \{z_h\}, \{r_h\}$", and "$V_b^{(i)^{-1}} \mid \{b_h^{(i)}\}, \Delta^{(i)}, \{z_h\}, \{r_h\}$" for $i = g, a, l$. The variance $s_{hp}^{(a)2}$ for $b_{hp}^{(a)} \sim N(0, s_{hp}^{(a)2})$ in the LPA was fixed as 0.01.

As for the posterior for the threshold parameters, conditional on $(b_h^{(i)}, \Lambda^{(i)})$, under the assumption of independent choice behavior across consumers, Terui and Dahana(2004) show that we have the conditional likelihood function of $\{r_h\}$ by taking products over respective consumers as

$$L(\{r_h\}; \{I_{ht}\}, \{X_{ht}\} \mid \{b_h^{(i)}\}, \{\Lambda^{(i)}\}) \propto \prod_{h=1}^{H} \left\{ \prod_{i=g,a,l} \left\{ \prod_{t \in R^{(i)}(r_h)} |\Lambda^{(i)}|^{-\frac{1}{2}} \exp\left\{ -\frac{1}{2} (y_{ht}^{(i)} - X_{ht}^{(i)} b_h^{(i)})' \Lambda^{(i)-1} (y_{ht}^{(i)} - X_{ht}^{(i)} b_h^{(i)}) \right\} \right\} \right\}.$$

and jointly with (4) expressed as hierarchical structure, we can apply Metropolis-Hasting sampling with random walk algorithm for price thresholds to obtain conditional posterior "$r_h \mid \{I_{ht}\}, \{X_{ht}\}, \{b_h^{(i)}\}, \Lambda^{(i)}, \{z_h\}, f, \Sigma_h$". Prior distributions and MCMC estimation procedures for these hierarchical Bayes models are described in Terui and Dahana(2004). Thus we have necessary conditional posterior distributions

(A-1)
$$\begin{cases} f \mid \{r_h\}, \{z_h\}, \Sigma_h : & \text{Nomal distribution} \\ \Sigma_h^{-1} \mid \{r_h\}, \{z_h\}, f : & \text{Inverted Wishart doistribution} \\ \{r_h\} \mid \{I_{ht}\}, \{X_{ht}\}, \{b_h^{(i)}\}, \Lambda^{(i)}, \{z_h\}, f, \Sigma_h : & \text{Metropolis-Hasting sampling} \end{cases}$$

Finally, we denote by $f_{(i)}\left(\{y_{ht}^{(i)}\},\{b_h^{(i)}\},\Lambda^{(i)},\Delta^{(i)},V_b^{(i)},\{r_h\},f,\Sigma_h \mid \{I_{ht}\},\{X_{ht}\},\{z_h\}\right)$ the joint posterior density for the regime i, and under the assumption of uncorrelated errors for latent utility equations of each regime, overall joint posterior density across regimes can be expressed as $\prod_{i=g,a,l} f_{(i)}\left(\{y_{ht}^{(i)}\},\{b_h^{(i)}\},\Lambda^{(i)},\Delta^{(i)},V_b^{(i)},r_h,f,\Sigma_h \mid \{I_{ht}\},\{X_{ht}\},\{z_h\}\right)$. In terms of sampling algorithms (A-1) for Markov chain Monte Carlo, we can constitute the posterior distribution of each regime respectively to get overall joint posterior density across regimes.

Incremental Sales and Profit

Conditional on the draw of $\left\{r_{1h}^{[s]}\right\}$ and $\left\{b_h^{(1)[s]},b_h^{(2)[s]}\right\}$ in the *s*-th iteration of MCMC, we set discounting level of $\left(r_{1h}^{[s]}+a\right)$(>0), ($a=0,\pm1,...,\pm5\%$) for $h=1,...,H$. Then, we evaluate the incremental sale for the consumer *h*

(A-2) $\Pr_j\left(b_h^{(1)[s]},P_{jh0}\left(1-\left(r_{1h}^{[s]}+a\right)\right)\right)-\Pr_j\left(b_h^{(2)[s]},P_{jh0}\right)$ if $a \ge 0$ for price gain

$\Pr_j\left(b_h^{(2)[s]},P_{jh0}\left(1-\left(r_{1h}^{[s]}+a\right)\right)\right)-\Pr_j\left(b_h^{(2)[s]},P_{jh0}\right)$ if $a<0$ for LPA

and these amounts are averaged over consumers to get the average in the market,

(A-3) $IS_j^{(-)}(a \mid \{(r_{1h}^{[s]},b_h^{(1)[s]},b_h^{(2)[s]}),h=1,...,H\})$.

This is iterated through *S* times to get the estimate of unconditional expected incremental sales

(A-4) $IS_j^{(-)}(a)=1/S\sum_{s=1}^{S}\left[IS_j^{(-)}(a \mid \{(r_{1h}^{[s]},b_h^{(1)[s]},b_h^{(2)[s]}),h=1,...,H\})\right]$.

The same operation is applied to the case of price hike to obtain the estimate of positive side $IS_j^{(+)}(a)$, and also those of expected profits $IP_j^{(-)}(a)$, $IP_j^{(+)}(a)$ and their difference $DIF_j^{(-)}(d^*)$, $DIF_j^{(+)}(d^*)$.

Figure 1: Price Threshold Model and Market Response

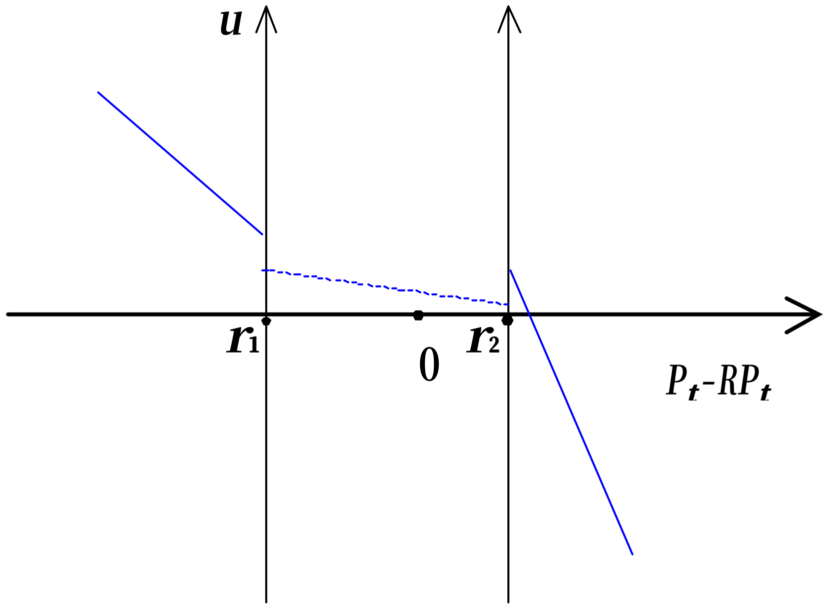

Table 1: Descriptive Statistics for Data

Alternative	Choice Share	Average Price	% of Time Displayed	% of Time Featured
Brand A	0.138	623.5	0.264	0.423
Brand B	0.480	632.9	0.135	0.294
Brand C	0.099	601.3	0.317	0.405
Brand D	0.225	693.2	0.182	0.344
Brand E	0.057	902.4	0.191	0.286

Figure 2: Heterogeneous Distribution of Price Thresholds

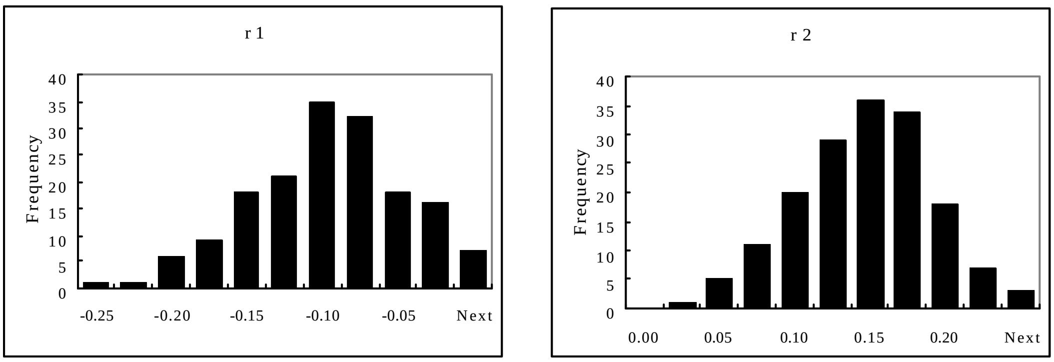

Figure 3: Expected Incremental Sales

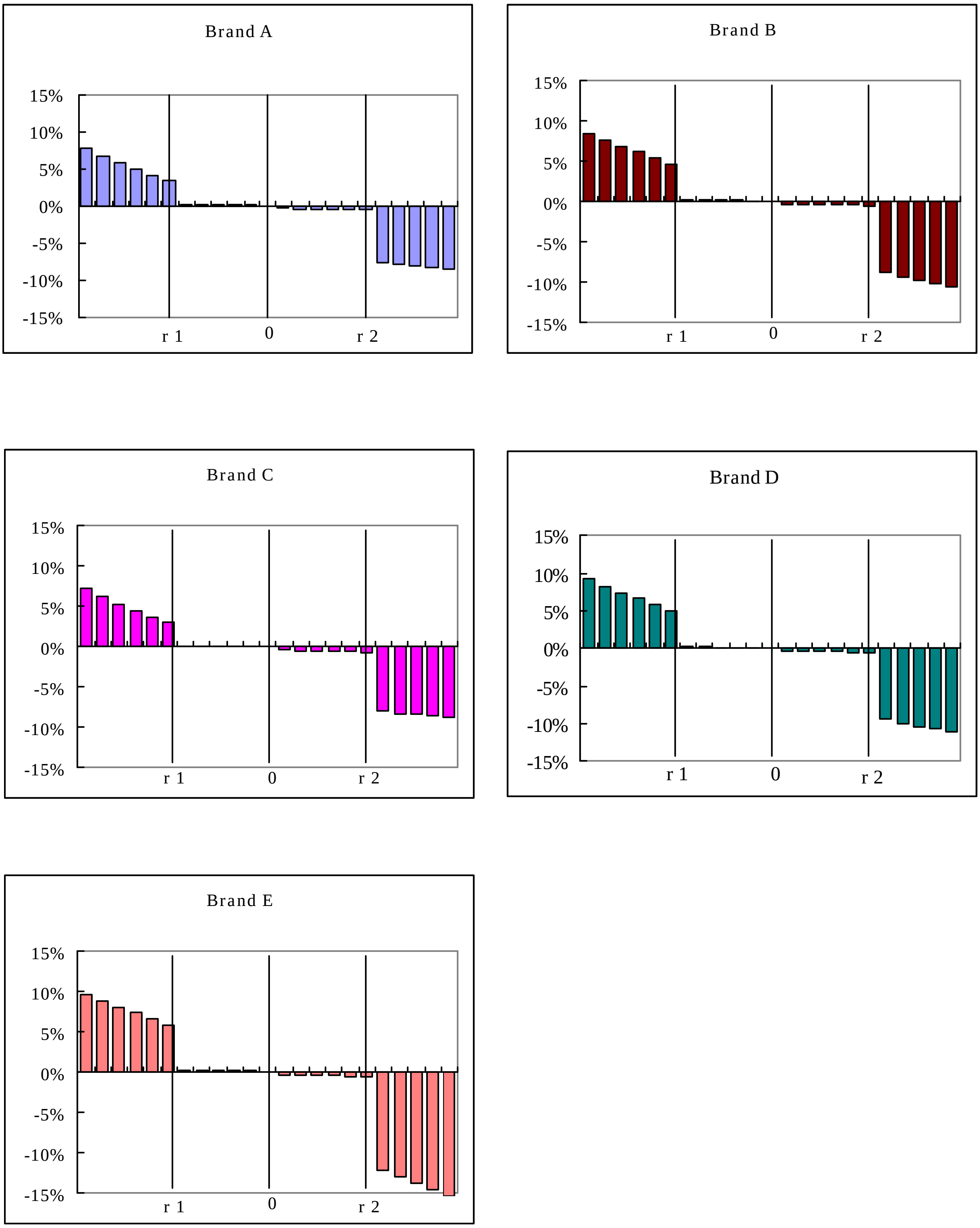

Figure 4: Expected Incremental Profits

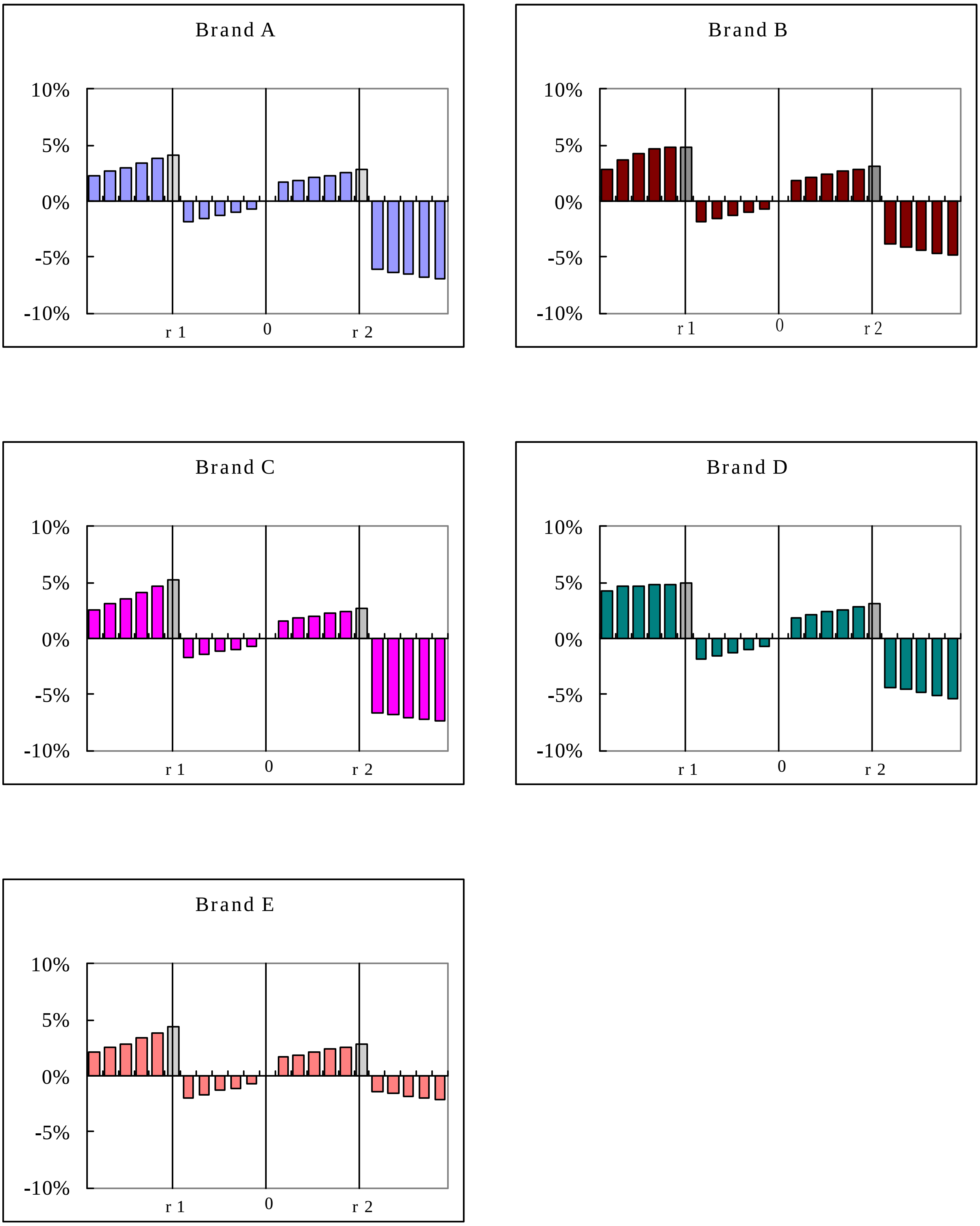

Figure 5: Difference of Incremental Profits

between Optimal Customized Pricing at (r_{1h}, r_{2h}) and Non-customized Pricing Strategies