Behavioral Price Discrimination in the Presence of Switching Costs

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Abstract

We study the strategic impacts of behavioral price discrimination on manufacturers and retailers in a distribution channel when there are switching costs in consumer demand. Unlike previous empirical studies of behavioral price discrimination, which rely only on differences in price elasticity across customers, our pricing model allows the strategies of channel members to additionally account for differences in price elasticity across time (due to switching costs). In our dynamic structural model, both wholesale and retail prices respond to past demand, as well as influence future demand, of all brands in the category. We apply our pricing model to empirical data from the cola category, which is a duopoly involving brands Coke and Pepsi. From the retailer’s price discrimination standpoint, we find that exploiting a consumer’s most recent brand choice (which is easily observed in the customer database) for pricing purposes yields as much profit dividend as exploiting the consumer’s latent segment membership information (which requires predictive analytics). We also find that the retailer should outsource the data analytics and price customization to manufacturers, by selling its customer database to them, in order to further improve retail profit. Interestingly, our results show that, while both manufacturers’ profits improve when they price discriminate based on segment membership, the weaker brand’s profit decreases when price discrimination takes in to account switching costs, when compared to the case of no price discrimination. This happens because of the incentive for each brand to “poach” its rival’s customers using lower prices. We also find that both manufacturers end up worse off under price discrimination when the retailer can sell its customer database to manufacturers, illustrating that customer information is a potent source of channel power to the retailer in markets with switching costs.

Keywords: Behavioral Price Discrimination, Dynamic Pricing, Targeted Coupons, Switching Costs, Inertia.
INTRODUCTION

Behavioral price discrimination (BPD henceforth) refers to the pricing strategy of firms charging different prices to different customers based on their past purchase behavior (Shaffer and Zhang 1995, Villas-Boas 1999, Fudenberg and Tirole 2000, Chen, Narasimhan and Zhang 2001, Acquisiti and Varian 2006, Pazgal and Soberman 2008, Shin and Sudhir 2010). This strategy is enabled by the fact that customers’ purchase histories are observed in retail transactional data collected by retailers using loyalty cards (such as the Kroger Rewards card). Using such customer-level transactional data, firms can estimate customer-specific price elasticities of demand and, therefore, tailor customer-specific retail prices using targeted coupons (see, for example, Elrod and Winer 1982, Rossi, McCulloch and Allenby 1996).

Previous empirical research on BPD has assumed that while price elasticities can vary across customers, a given customer’s price elasticity is time invariant. However, an extensive empirical literature in marketing has documented that on account of switching costs in demand, a customer’s price elasticity for the most recently purchased brand decreases at her next purchase occasion (see, for example, Seetharaman 2004). This means that while determining the optimal BPD strategy, the retailer must recognize differences in brands’ price elasticities not only across customers but also across time (due to switching costs). Taking switching costs into account, firms can better tune their BPD schemes by offering the right coupons not only to the “right customers” but also at the “right time.”

One pricing implication of switching costs in demand is that manufacturers or retailers can target price-off coupons to consumers that are based on their most recently purchased brands. Suppose that the brand manager of Coke observes that John Doe’s most recently purchased brand in the cola category is Pepsi. She will realize that, on account of switching costs, she should offer John Doe a price discount on Coke in order to induce him to buy Coke instead of Pepsi. While John Doe may not be price sensitive, offering him a coupon can still be profitable to Coke because, once John Doe buys Coke, he will be more likely to buy Coke again in the future. This future sales gain can dominate the cost of current price discount. The brand manager of Pepsi faces a similar incentive to lure previous buyers of Coke using price discounts. Whether such competitive pressures, which force firms to “poach” each other’s
customers (Chen 1997, Shaffer and Zhang 2000, Taylor 2003), could dominate the incentive to “milk” the installed customer base (i.e., most recent buyers) by charging higher prices, is an interesting empirical question. Previous empirical studies on BPD have concluded that competing firms benefit from BPD (Besanko, Dube and Gupta 2003, Pancras and Sudhir 2007). In this research, we study BPD in an oligopoly in the presence of switching costs. In doing this, we are able to analyze the inter-play between the “poaching” and “milking” incentives discussed above and, therefore, understand whether the inter-play yields different implications for different brands.

When studying BPD in an oligopoly, the strategic role of the retailer cannot be ignored (Liu and Zhang 2006). However, previous research on BPD in markets with switching costs has ignored the role of the retailer. This is a serious limitation on account of two reasons. First, being a category profit maximizer, the retailer’s pricing incentive may not align with the manufacturers’ pricing incentives; this means that the profit implications of BPD derived for competing manufacturers may unravel in the presence of the retailer. Second, even if manufacturers can effectively by-pass the retailer by dropping direct-mail targeted coupons to end-consumers (in order to successfully reap the benefits of BPD), the retailer can put paid to such efforts by not sharing its customer database with the manufacturers, which makes it impossible for the manufacturers to estimate customer-specific price elasticities (which are necessary for engaging in BPD). It is also logistically easier for the retailer to offer coupons to consumers at the store than for a manufacturer to mail coupons to consumers’ homes. In this research, we study BPD within the distribution channel in a market with switching costs. In doing this, we are able to answer the question of whether it is profitable for the retailer to share its customer information with manufacturers and letting them engage in BPD instead of managing the BPD by itself.

We take an empirical approach. We rely on structural estimates of consumer demand and firm pricing behavior, obtained for a duopoly market using actual market data on demand and prices, to perform counterfactual experiments regarding BPD, in which the retailer or manufacturers may target their prices based on either customers’ segment memberships or customers’ most recently purchased brands. Our key findings are as follows: First, we document substantively significant differences in brand-
specific price elasticities over time due to switching costs. Second, we find that the retailer can more than double their incremental profit from BPD by exploiting the most recent purchase information of each customer in addition to their segment membership, when compared to exploiting segment membership only. This means that a large increase in retail profit could accrue at little to no analytical cost since tracking the most recent purchase outcome of a customer is very easy from a database management standpoint for a retailer. We also find that the retailer gains more from targeting prices based on customers’ most recent purchases than from targeting prices based on customers’ segment memberships. It is remarkable that such a meaningful retail profit lift can be obtained by using just a simple summary statistic (i.e., most recent choice) about consumer behavior. Third, we find that when the retailer engages in BPD, manufacturer profit increases for the larger manufacturer (Pepsi) but decreases for the smaller manufacturer (Coke). Furthermore, we find that when both manufacturers employ BPD instead of the retailer (when the retailer shares the customer information with both manufacturers at no charge), both manufacturers benefit when the BPD is based on customers’ segment memberships only. However, when the BPD is based on both customers’ segment memberships, as well as customers’ most recent purchases, the smaller manufacturer (Coke) hurts even though the profits of the larger manufacturer (Pepsi) slightly increase. This is because the increased targeting ability creates a strong incentive for each firm to “poach” its rival’s customers which intensifies price competition among the firms.

Finally, we find that the retailer’s profit increases when both manufacturers jointly employ BPD, as opposed to the retailer employing BPD by itself. In other words, when BPD is feasible, the retailer should simply outsource the data analytics and customization of coupons to manufacturers and improve its profit beyond what it can achieve by proactively engaging in analytics and customization on its own. If the retailer can charge the manufacturers for access to its customer database, its profit improves further. In other words, serving as an information broker to sell transactional data to product manufacturers can be a vital source of business profit to the retailer (see Glazer 1991 for an early view on information as a business asset). However, the manufacturers end up being worse off than under the case of no price
discrimination! This is a new finding to the literature on BPD. It illustrates that information is a potent source of channel power to the retailer in the presence of switching costs.

**BEHAVIORAL PRICE DISCRIMINATION IN THE PRESENCE OF SWITCHING COSTS**

We consider a monopolist retailer in a local market. There are \( J \) major manufacturers (Coca Cola and Pepsi in our application) selling their brands through the retailer. We assume a three-stage game: in the first stage (at the start of the game), the retailer, as the owner of the customer database which contains customers’ purchasing histories, decides whether to directly engage in BPD by exploiting the information in the customer database, or to share the information with the manufacturers and help them employ BPD by distributing targeted coupons, whose values they will determine, directly to consumers; in the second stage of the game, the manufacturers simultaneously choose wholesale prices for their brands and, if feasible, price-off coupons targeting different types of customers; in the third stage, taking the manufacturers’ pricing and couponing decisions as given, the retailer chooses retail prices for the brands and, if feasible, price-off coupons targeting different customers.

Let \( S_{jt}^m \) denote a state variable that represents the segment \( m \)-specific (\( m = 1, ..., M \)) installed base, i.e., share of customers in latent segment \( m \) (based on their time-invariant utility parameters that will be described below) whose most recent purchase in the category was brand \( j \) (\( j = 1, ..., J \)), as of period \( t \) (\( t=1, ..., T \)). The set of state variables that determines manufacturers’ and the retailer’s BPD strategy is

\[
S_t = \{S_{t1}^1, S_{t2}^1, ..., S_{t2}^J, ..., S_{tM}^M, S_{t2}^M, ..., S_{tJ}^M \},
\]

i.e., the collection of the installed bases of \( J \) brands within each of the \( M \) consumer segments. The objective of each firm in the channel is to maximize its long-term discounted profit. We assume that manufacturers compete in an infinitely repeated Bertrand pricing game and focus our attention on Pure-Strategy Markov-Perfect Equilibria (MPE), noting that there could be multiple such equilibria. Let \( a_j \) be the set of control variables for manufacturer \( j \), which defines its BPD strategy. Suppose the manufacturer obtains customer information from the retailer in the first stage and, therefore, can identify that a customer belongs to \( S_{it}^m \), i.e., that the customer belongs to latent segment \( m \)
and bought brand $k$ during his previous purchase. The manufacturer can issue a coupon, $C_{mft_{jkt}}$, to such a customer whose face value will be deducted from the retail price of brand $j$ when the customer purchases brand $j$ in period $t$. $C_{mft_{jkt}}$ will directly impact the per-unit revenue for the manufacturer, $w_{jkt}$, and the “real” price (i.e., retail price minus coupon) that the customer has to pay for buying the brand, $p_{jkt}$. The manufacturer also has to decide wholesale price $W_{jt}$; thus, the set of control variables is $a_{jt} = \{W_{jt}, C_{mft_{jkt}}, m = 1, ..., M, k = 1, ..., J\}$. If the retailer decides to directly engage in BPD, the retailer can issue targeted coupons, $C_{Ret_{jkt}}$, $\forall j$ to customers in latent segment $m$ whose previously purchased brand was $k$. The coupon will impact the per-unit revenue for the retailer, $r_{jkt}$, and the “real” price that the customer has to pay for buying the brand, $p_{jkt}$. The set of control variables of the retailer is $a_{Rt} = \{P_{jt}, C_{Ret_{jkt}}, m = 1, ..., M, j, k = 1, ..., J\}$, where $P_{jt}$ is the retail price.

Let $a_t = \{a_{Rt}, a_{jt}, j = 1, ..., J\}$ be the collection of control variables of the retailer and all manufacturers in the second and third stages of the pricing game. In the presence of switching costs, current decisions $a_t$ will have a dynamic impact on the state variables in the next period, $S_{t+1}$. The following equation, called the state equation, captures the temporal evolution of the state variable, $S_{jt}$.

$$S_{j,t+1} = \sum_{k \neq j} S_{j,t}^m \cdot Pr_j^m (k \rightarrow j \mid a_t) + S_{j,t}^m \cdot \left( Pr_j^m (j \rightarrow j \mid a_t) + Pr_j^m (j \rightarrow 0 \mid a_t) \right),$$

where $Pr_j^m (k \rightarrow j \mid a_t)$ stands for the switching probability, for a customer in segment $m$, of switching from brand $k$ to brand $j$, conditional on $a_t$; $Pr_j^m (j \rightarrow j \mid a_t)$ stands for the customer’s repeat purchase probability for brand $j$, conditional on $a_t$; and $Pr_j^m (j \rightarrow 0 \mid a_t)$ stands for the probability of the customer choosing the outside option, conditional on $a_t$, in which case the customer remains in the installed base of brand $j$. This equation suggests that brand $j$’s installed base in a given period is a sum of two types of customers: one, those who bought brand $j$ in the previous period; two, those who did not buy any brand in
the previous period but whose most recently purchased brand was brand \( j \). We use the inertial multinomial logit model (Seetharaman, Ainslie and Chintagunta 1999) to represent the brand choice probabilities, i.e., switching probability and repeat purchase probability, and include the outside option in the usual manner as a \((J+1)\)th alternative, with a deterministic utility of zero.

Given equation (1) that governs the evolution of the state variable, \( S_{jt}^m \), the aggregate-level brand demand for brand \( j \) in week \( t \), \( D_{jt}(a_j) \), is

\[
D_{jt}(a_j) = \sum_{m=1}^{M} \pi_m \cdot \sum_{k=1}^{J} \Pr_{tm}^m (k \rightarrow j | a_j),
\]

where \( \pi_m \) is the size of latent segment \( m \). The demand function then serves as an input to a supply-side model dealing with dynamic pricing decisions within a distribution channel.

We assume that manufacturers and the retailer have a common discount factor \( \rho < 1 \), and for each manufacturer \( j \), the discounted sum of profits can be written as the following Bellman equation.

\[
V_j(S) = \max_{a_j} \left\{ \sum_{m=1}^{M} \pi_m \cdot \sum_{k=1}^{J} \left[w_{jk}^m \left( a_j, a_{-j} \right) - mc_j \right] \cdot S_{k}^m \cdot \Pr_{tm}^m (k \rightarrow j | a_j, a_{-j}) + \rho \cdot EV_j(S' | S, a_j, a_{-j}) \right\},
\]

where \( V_j(S) \) is the value function of the manufacturer under optimal policies, \( a_j \) represents the policies of other players (i.e., other manufacturers and the retailer), \( S_{k}^m \) is the installed base of customers in latent segment \( m \) for brand \( k \), and \( S \) and \( S' \) are the state variables in the current and next period, respectively, \( w_{jk}^m \left( a_j, a_{-j} \right) \) represents the actual revenue per unit sold for the manufacturer and is equal to the wholesale price minus the value of the coupon issued to customers in segment \( m \) whose previously purchased brand was \( k \), and \( mc_j \) is the marginal production cost for the manufacturer that will be specified later.

Similarly, the retailer’s discounted sum of profits can be written as

\[
V_R(S) = \max_{a_R} \left\{ \sum_{m=1}^{M} \pi_m \cdot \sum_{j=1}^{J} \sum_{k=1}^{K} \left[r_{jk}^m \left( a_R, a_{-R} \right) - W_j \right] \cdot S_{k}^m \cdot \Pr_{tm}^m (k \rightarrow j | a_R, a_{-R}) + \rho \cdot EV_R(S' | S, a_R, a_{-R}) \right\},
\]

where \( V_R(S) \) is the value function of the retailer under optimal policies, \( a_R \) represents the policies of other players (i.e., all manufacturers), \( r_{jk}^m \left( a_R, a_{-R} \right) \) stands for the actual revenue per unit sold for the retailer
and is equal to the retail price minus the value of the coupon issued to customers in segment $m$ whose previously purchased brand was $k$, and $W_j$ is the wholesale price charged by manufacturer $j$.

To investigate the implications of BPD on the pricing behavior and resulting profits of the manufacturers and the retailer, we study the different scenarios that correspond to different retailer decisions in the first stage regarding how to use the customer information. The different scenarios allow different members of the distribution channel to employ BPD. As each firm’s pricing policy has strategic consequences for other channel members’ pricing policies, we use the full equilibrium approach to examine the MPE pricing outcomes within each scenario.

**Scenario 1: No Couponing (Base Case)**

This is the benchmark case. Manufacturers and the retailer do not use targeted coupons. This is the typically assumed channel structure in the marketing literature (see, for example, Sudhir 2001).

**Scenario 2: Couponing Based on Segments Only**

**Case 1: Retailer Couponing:** The retailer infers customers’ segment memberships from the entire history of past purchases. For each brand, the retailer issues different coupons to different customers based on their segment memberships only, as in Pancras and Sudhir (2007). See Figure 1.

**Case 2: Both Coke and Pepsi Couponing:** The retailer shares the customer information with both manufacturers and lets them directly employ BPD. Manufacturers issue coupons to customers based on their segment memberships only, as in Pancras and Sudhir (2007). See Figure 2.

**Scenario 3: Couponing Based on Segments and Most Recently Purchased Brands**

**Case 1: Retailer Couponing:** The retailer accounts for not only customers’ segment memberships but also their most recently purchased brands, while issuing coupons to customers. See Figure 3.

**Case 2: Both Coke and Pepsi Couponing Based on Segments and Most Recently Purchased Brands**
The retailer shares customer information with the manufacturers, and manufacturers issue coupons to customers based on their segment memberships and most recently purchased brands. See Figure 4. We study 3 sub-cases, as explained below.

a. Both Coke and Pepsi Couponing

b. Exclusive Coke Couponing: The retailer shares customer information with Coke only.

c. Exclusive Pepsi Couponing: The retailer shares customer information with Pepsi only.

Scenario 4: Couponing Based on Most Recently Purchased Brands Only

This is similar to Scenario 2, except that the coupons are based only on customers’ most recently purchased brands, which capture the effects of switching costs, and not on customers’ segment memberships.

Case 1: Retailer Couponing

Case 2: Both Coke and Pepsi Couponing

EMPIRICAL RESULTS

We use scanner panel data from Information Resources Incorporated’s (IRI) scanner-panel database on cola purchases of 356 households making 32942 shopping trips at a supermarket store (which is a local monopolist) in a suburban market of a large U.S. city from June 1991 to June 1993. The 356 households purchase cola during 5784 (17.56%) of their shopping trips, and choose among Pepsi, Coke, Royal Crown and a private label. Pepsi is the dominant cola brand (with an average market share of 0.4567), while the Private Label is the smallest brand (with an average market share of 0.0685).

In our data, neither manufacturers nor the retailer uses BPD, which is the base case in Scenario 1.

We first estimate demand parameters \( \{\alpha_f^m, \beta_1^m, \beta_2^m, \beta_3^m, \lambda_{BD}^m\}; m = 1, ..., M \), using the panel data on
households’ brand choices.\textsuperscript{1} We identify a small Segment 1 (29 \% of households) of heavy users, whose marketing mix sensitivities (-5.233 for price, 1.113 for display, 0.228 for feature) are smaller than those of a large Segment 2 (71 \%) of light users (-6.727, 1.454, 0.320).\textsuperscript{2} Segment 1 has higher switching costs than Segment 2, which manifests as follows: Pepsi’s price elasticity in segment 1 decreases from -3.72 (when Coke was bought previously) to -2.99 (when Pepsi was bought previously), while the corresponding decrease in segment 2 is relatively modest (-5 to -4.93). Similarly, Coke’s price elasticity in segment 1 decreases from -4.07 (when Pepsi was bought previously) to -3.48 (when Coke was bought previously), while the corresponding decrease in segment 2 is relatively modest (-5.39 to -5.35).

For the pricing model, we assume that Coke and Pepsi directly compete against each other and that their pricing strategies are independent of the pricing strategies of RC Cola and the Private Label.\textsuperscript{3} For manufacturer \( j \) in week \( t \), the marginal cost is \( mc_{jt} = C_j + \nu_{jt} \), where \( C_j \) is the average marginal cost of brand \( j \), and \( \nu_{jt} \sim iid N (0, \sigma_j^2) \) is a cost shock, which is observed by the firms but not by the researcher, of brand \( j \) in week \( t \). We estimate the pricing model using the value functions (3) and (4), using observed weekly prices in our data. In doing this, we use the estimated aggregate-level demand for each brand, which is based on the demand estimates, as an input in the value functions. We adopt GMM for estimation (see Cosguner, Chan and Seetharaman 2014 for details). The estimated marginal costs of Coke and Pepsi turn out to be $0.436 and $0.355, which translate to estimated channel profit margins of $0.369 (85 \%) and $0.395 (111 \%), respectively.

Given the estimated demand and supply parameters, we run a series of counterfactual simulations to study the different price discrimination scenarios described in the model section. For these simulations, we use a modified version of the Pakes and McGuire (1994) algorithm in order to solve for

\textsuperscript{1} Since only 4.5 \% of the purchases in our data involve the simultaneous purchase of Coke and Pepsi, the discrete choice assumption holds in our data. We assume that households are static utility maximizers. We do not find evidence of higher order state dependence (i.e., beyond the most recent lag) in the data.

\textsuperscript{2} Under a 3-segment specification, we find that the size of the third segment (10 \%) is quite small when compared to the other two segments (56 \%, 34 \%). Therefore, the profit gains from exploiting additional customer heterogeneity beyond two segments would be limited to manufacturers and retailers.

\textsuperscript{3} We use price regressions to test this duopoly assumption. Results show that the impacts of the prices of RC and Private Label on the prices of Coke and Pepsi are very small.
the dynamic pricing equilibrium in the distribution channel. We assume that no customer is in any brand’s installed base in the first period, and forward simulate retail prices, wholesale prices and customers’ brand choices for multiple future periods, until the prices and the associated demands reach a steady state. Since there are two latent customer segments in the cola market under study, in the scenarios where the retailer or manufacturers employ BPD based on latent segments only, only one segment receives price-off coupons and the other segment has to pay retail prices. In each scenario, we find that it is more profitable to offer coupons to the more price sensitive segment (in our case, segment 2). In the scenarios where BPD is based on both latent segments and most recently purchased brands, for each brand there are four types of customers, depending on their segment membership (segment 1 or 2), and previously purchased brand (focal or competitor). Among these 4 customer types, we find that the only type that should pay retail prices are segment 1 customers whose last purchase was the focal brand, while the other 3 types should be offered price-off coupons of varying face values. In these simulations, we infer segment membership from a customer’s past purchases using Bayes rule (Kamakura and Russell 1989).

We first simulate, in the steady state, the equilibrium retail and wholesale prices, and each channel member’s NPV of the profit stream, averaged across customers, under the assumption that the same prices are offered to both latent segments, i.e., Scenario 1. Under this scenario, manufacturers first charge the retailer wholesale prices $W_{Coke}$ and $W_{Pepsi}$, and then the retailer charges end consumers retail prices $P_{Coke}$ and $P_{Pepsi}$. The second column in Table 1 reports the retail and wholesale prices, as well as the profits of all channel members. Since Pepsi has lower average marginal cost and higher brand preference than Coke, it enjoys a higher profit than Coke. In addition, the retailer as a local monopolist enjoys a higher profit than the combined profits of Pepsi and Coke. Next, we simulate the equilibrium outcomes under the assumption that the retailer offers customized coupons to customers based on their segment memberships, (Scenario 2, Case 1; see Figure 1). In practice, the retailer can distribute these coupons at check-out counters inside the store. The results are shown in the third column of Table 1. Compared to the base case, segment 1 customers now face a higher retail price but, after deducting the coupon values, segment 2 customers enjoy a lower price. Comparing columns 2 and 3, we find that the retailer and Pepsi
both benefit (with their profits increasing by 4.8 % and 6.8 %, respectively), while Coke hurts (with its profit decreasing by 1.6 %), from the retailer’s targeted pricing efforts. This is because the retailer enjoys a higher margin from selling Pepsi products; therefore, it has an incentive to offer segment 2 customers a lower price for Pepsi, which decreases the sales and, therefore, the profits of Coke.

We next simulate the equilibrium outcomes under the assumption that the retailer offers customized coupons to each customer based on not only their segment membership but also their most recently purchased brand (Scenario 3, Case 1; see Figure 2). In practice, these coupons can be restricted to be redeemable within the length of a typical purchase cycle (the median inter-purchase cycle is 5 weeks in our data). The results are shown in the fifth column of Table 1. Comparing columns 2 and 5, we find that the retailer and Pepsi both benefit (with their profits increasing by 10.2 % and 5 %, respectively), while Coke hurts (with its profit decreasing by 3.3 %), from the retailer’s ability to offer different retail prices to different customer segments. The reason for this result is as explained in the previous paragraph. Comparing columns 3 and 5, we find that the retailer more than doubles their incremental profit from price discrimination (10.2 % versus 4.8 % improvement) by also exploiting the previous purchase information of each customer in addition to their segment membership. This is a new finding to the literature on BPD. This increase in retail profit could accrue at little to no analytical cost since tracking the most recent purchase outcome of a customer is very easy from a database management standpoint for the retailer. Some, but not most, of this additional retail profit comes at the expense of the manufacturers whose profits decrease slightly from column 3 to 5.

We next assume that the retailer shares its customer information (at no charge) with both manufacturers and helps them employ BDP instead. To facilitate the implementation, manufacturers may get help from the retailer to distribute their coupons at check-out counters inside the store. The fourth and sixth columns in Table 1 show the results for the cases of targeting based on customer segments only (Scenario 2, Case 2), and based on both segments and most recently purchased brands (Scenario 3, Case 2), respectively. Compared to the base case (column 2), the profit of Pepsi increases by 11.6 %, while that of Coke increases by 6 %, from couponing based on segment membership (column 4). By additionally
exploiting the most recent purchase, the profit of Pepsi increases by an additional 0.8 % (column 6). However, Coke’s profit decreases by 2 % even compared to the base case. This finding is consistent with the analytical result in Chen, Narasimhan and Zhang (2001) that increasing the degree of targetability of a coupon may hurt manufacturer profit, although we uncover it only for the smaller manufacturer (Coke), but not for the larger manufacturer (Pepsi). This is because increased targeting ability increases each manufacturer’s incentive to “poach” its rival’s customers by offering lower prices using targeted coupons; this decreases Coke’s profit margin sufficiently to overwhelm its ability to “milk” its own customers by charging them higher prices.

To further investigate the relative impacts of targeting based on different types of customer information, we simulate equilibrium outcomes when targeting is based on customers’ most recent purchases only (Scenario 4) and the results are shown in the last two columns of Table 1. When the retailer employs BPD (Scenario 4, Case 1), its profit increases by 5.5 % (compared to the base case), which is higher than the 4.8 % increase obtained from BPD that is based on segment memberships only (column 3). Considering that tracking the most recent purchase of each customer in the retailer’s data warehouse is a much easier task than calculating the segment membership (using the customer’s full purchase history), it is remarkable that such a meaningful retail profit lift can be obtained by the retailer using such a simple summary statistic about customer behavior. This finding is reminiscent of the power of RFM statistics in database marketing and CRM applications (see, for example, Fader, Hardie and Lee 2005). For manufacturers, while the profit of Coke remains almost the same, the profit of Pepsi drops by 2.3 %. The main reason is that Pepsi has to charge a lower wholesale price because the ability to engage in BPD gives the retailer stronger market power in the channel.

When the retailer shares the information on customers’ most recent purchases with manufacturers and helps them employ BPD (Scenario 4, Case 2), the profit of Pepsi improves by 3 % (compared to the base case). However, the profit of Coke drops by 17 %. In other words, BPD that is based only on customers’ most recent purchases benefits the larger manufacturer but hurts the smaller manufacturer. This is in contrast to our earlier finding that BPD that is based only on customers’ segment memberships
(column 4) benefits both manufacturers. That said, even the larger manufacturer, Pepsi, achieves a higher profit when targeting based on segment memberships only (column 4) than in this case. However, the retailer achieves higher profit in this case than when targeting is based on segment memberships only (columns 3 versus 9). This asymmetry between the manufacturers and the retailer in the strategic value of BPD that is based on most recent purchases only further shows that the retailer appears to be in a position of power in the distribution channel.

Next, we use the simulation results to answer the question, from the retailer’s vantage point, of which channel member should employ such price-off couponing strategies. Specifically, should the retailer employ BPD by itself, or share information with manufacturers and help them employ BPD instead? Comparing columns 5 and 6 of Table 1, we find that the retailer benefits (with its profit increasing by a further 0.5 %) when both manufacturers employ BPD (i.e., Scenario 3, Case 2), as opposed to the retailer employing BPD by itself (i.e., Scenario 3, Case 1). To throw more light on this, we study two additional cases: (i) Only Coke drops customized coupons (i.e., Scenario 3, Case 2a), and (ii) Only Pepsi drops customized coupons (i.e., Scenario 3, Case 2b). The simulation results for these two cases are reported in columns 7 and 8 of Table 1. We find that the retailer’s profits under both of these cases are lower than in column 6 when both manufacturers jointly drop customized coupons. In fact, the profits are also lower than those obtained when the retailer employs BPD by itself (column 5). In sum, the equilibrium outcome in the three-stage game in our model is that, when BPD is feasible, the retailer will simply outsource the data analytics and customization of coupons to the two manufacturers and improve its profit beyond what it can achieve by proactively engaging in analytics and customization on its own!

The above analyses assume that the retailer shares the customer information with the manufacturers and helps them distribute coupons at no charge. We next explore whether the above implications change if the retailer can charge manufacturers for access to its customer database, that is, if the retailer can serve as an information broker and sell information to manufacturers (as in Pancras and Sudhir 2007). In order to answer this question, we first calculate the highest price that the retailer can charge each manufacturer, which represents the manufacturer’s willingness to pay, for access to the
retailer’s customer database, under the case when both manufacturers engage in targeted couponing (i.e., Scenario 3, Case 2). We employ the Nash equilibrium solution concept as follows: The highest price to charge Coke is the additional profit that Coke obtains under Scenario 3, Case 2 (column 6) relative to Scenario 3, Case 2b (when only Pepsi drops customized coupons; column 8). The highest price to charge Pepsi is the additional profit that Pepsi obtains under Scenario 3, Case 2 (column 6) relative to Scenario 3, Case 2a (when only Coke drops customized coupons; column 7). With this calculation, the retailer can charge $0.0268 (= $0.2210 - $0.1942) to Coke and $0.1375 (= $0.5929 - $0.4554) to Pepsi, per customer, for access to its customer database. Suppose the retailer makes the following take-it-or-leave-it offer to the manufacturers: “I will charge $0.0268 ($0.1375) to Coke (Pepsi) per customer for the use of my customer database.” If both Coke and Pepsi accept the offer, they end up making profits of $0.2210 - $0.0268 = $0.1942 and $0.5929 - $0.1375 = $0.4554, respectively. Suppose Coke accepts the offer, but Pepsi declines. In this case, Coke and Pepsi make profits of $0.2862 - $0.0268 = $0.2594 and $0.4554, respectively. This leaves Coke better off, but not Pepsi, compared to the case of both manufacturers accepting the retailer’s take-it-or-leave it offer. Therefore, Pepsi has no incentive to decline the offer if Coke accepts the offer. Likewise, Coke has no incentive to decline the offer if Pepsi accepts the offer. Furthermore, since $0.2594 and $0.5068 are higher than $0.1942 and $0.4554, respectively, each manufacturer is strictly better off by accepting the retailer’s offer when its competitor rejects the offer. This means that both Coke and Pepsi will accept the retailer’s take-it-or-leave-it offer for access to the retailer’s customer database.

Once we account for the above, we find that the retailer will be much better off outsourcing the customized couponing strategy to manufacturers, with a net profit of $1.1660 (= $1.0017 + $0.0268 + $0.1375), which represents a 17% increase over the profit obtained by managing BPD on its own (which itself is 12% higher than the profit obtained in the base case, i.e., Scenario 1)! In other words, serving as an information broker to sell transactional data to product manufacturers can be a vital source of business profit to the retailer. This finding is consistent with the findings in Pancras and Sudhir (2007), although they use a myopic pricing model in their study. Interestingly, this yields net profits to Coke and
Pepsi of $0.1942 and $0.4554, respectively, which are both lower than their profit counterparts under Scenario 1 (column 2). In other words, while the retailer benefits from inducing manufacturers to behaviorally price discriminate by dropping customized coupons to different customer types, it ends up making the manufacturers worse off than under the case of no price discrimination! This is in contrast to the situation in Pancras and Sudhir (2007), where the authors find that manufacturers’ profits improve, relative to the case of no price discrimination, along with the retailer’s profit. *Our finding illustrates that information is a potent source of channel power to the retailer in the presence of switching costs.*

**CONCLUSIONS**

We study behavioral price discrimination (BPD), using targeted price-off coupons, within a distribution channel in a market with switching costs. Our study delineates the separate strategic roles of the manufacturers and the retailer. Our key findings are as follows. First, we find that the retailer can more than double their incremental profit from BPD by exploiting the most recent purchase information of each customer in addition to their segment membership, when compared to exploiting segment membership only. This increase could accrue at little to no analytical cost since tracking the most recent purchase outcome of a customer is very easy from a database management standpoint for a retailer. Second, we find that when the retailer engages in BPD, manufacturer profit increases for the large manufacturer (Pepsi) but decreases for the small manufacturer (Coke). Third, we find that when both manufacturers employ BPD instead of the retailer (when the retailer shares the customer information with both manufacturers and helps them distribute coupons at no charge), both manufacturers benefit when the BPD is based on customers’ segment memberships only. However, when the BPD is also based on customers’ most recent purchases, the smaller manufacturer (Coke) hurts even though the profits of the larger manufacturer (Pepsi) slightly increase. Finally, we find that the retailer benefits (i.e., retail profit increases) when both manufacturers jointly employ BPD, as opposed to the retailer employing BPD by itself. If the retailer can charge the manufacturers for access to its customer database, its profit improves further. However, the manufacturers end up being worse off than under the case of no price discrimination.
discrimination! This illustrates that information is a potent source of channel power to the retailer in the presence of inertial demand.

Some caveats remain. First, we ignore the potential endogeneity of price, display and feature while estimating our brand choice model. Identifying appropriate instruments to correct for such endogeneity is beyond the scope of this study and, more importantly, not germane to the focus of this research. Second, we assume that coupon redemption rates are equal across customer segments. In reality, it is possible that more price sensitive customers are more likely to redeem coupons. If such were the case, our key results (such as, for example, that higher face value coupons must be dropped to more price sensitive customers) would be strengthened. An interesting area of future research would be to study whether consumer preferences evolve over time and the consequences of ignoring such preference evolution on the inferences obtained in this study. Another interesting area of future research would be to study the BPD implications of consumer variety seeking and stockpiling behavior.
REFERENCES


Figure 1: (Scenario 2; Case 1) Dynamic Channel Pricing with Retailer Couponing Based on Segments

Figure 2: (Scenario 2; Cases 2a, b, c) Dynamic Channel Pricing with Manufacturer Couponing Based on Segments
Figure 3: (Scenario 3; Case 1)
Dynamic Channel Pricing with Retailer Couponing Based on Both Segments and Past Purchases

Figure 4: (Scenario 3; Cases 2a, b, c)
Dynamic Channel Pricing with Manufacturer Couponing Based on Both Segments and Past Purchases
<table>
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<tr>
<th>Variable</th>
<th>Scenario 1: No targeting (No Coupon)</th>
<th>Scenario 2: Targeting based on segment membership only</th>
<th>Scenario 3: Targeting based on segment membership and most recent purchase</th>
<th>Scenario 4: Targeting based on most recent purchase only</th>
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