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Zuzana Brokesova

Cary Deck
Chapman University, deck@chapman.edu

Jana Peliova

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Zuzana BROKESOVA[a], Cary DECK[b], Jana PELIOVA[c]

[a] Corresponding author, Faculty of National Economy, University of Economics in Bratislava, Dolnozemska cesta 1, 852 35 Bratislava, Slovak Republic, zuzana.brokesova@euba.sk, +421 2 672 91 562

[b] Sam M. Walton College of Business, University of Arkansas, Fayetteville, AR 72701, United States & Economic Science Institute, Chapman University, One University Drive, Orange, CA 92866, United States, cdeck@walton.uark.edu

[c] Faculty of National Economy, University of Economics in Bratislava, Dolnozemska cesta 1, 852 35 Bratislava, Slovak Republic, peliova.jana@euba.sk

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Experimenting with Behavior Based Pricing

Abstract

Many purchases of differentiated goods are repeated, giving sellers the opportunity to engage in price discrimination based upon the shopper's previous behavior by either offering loyalty discounts to repeat buyers or introductory rates to new customers. Recent theoretical work suggests that loyalty discounts are likely to be implemented when customer preferences are not stationary and sellers can pre-commit to prices for repeat buyers, but otherwise repeat buyers can be expected to pay the same or more than new buyers. This paper reports the results of a series of controlled laboratory experiments designed to empirically test the impact of these factors on pricing strategies, seller profit and total cost to consumers. Absent price pre-commitments, sellers in the lab engage in poaching when it is optimal to do so, but the ability to pre-commit leads to prices being relatively more favorable to loyal customers. Customer poaching increases seller profit and increases total consumer costs in the case of stable consumer preferences without price pre-commitment.

Keywords: Loyalty Discounts, Poaching, Repeat Purchases, Price Discrimination

JEL codes: C71, C91, D41

Introduction

Sellers have long engaged in various forms of price discrimination (see Stole, 2007; Varian, 1989). However, recent technological advances give sellers even more information about their customers including the ability to track people across shopping episodes. This enables sellers, both online and in bricks and mortar stores, to identify which customers are making a repeat visit and which are new. With such information sellers can either attempt to reward loyalty or poach from rivals. Indeed, both practices are now commonly observed. Many airlines and retailers offer perks to loyal customers, while credit cards and insurance companies commonly advertise low introductory rates to new customers. In each of these cases sellers are basing prices on the shopper's previous behavior.

Caillaud and De Nijs (2011, p. 1) define the practice of "offering different prices to different customers according to their past purchase history" as *behavior based pricing* (BBP). This practice, which does not fit any of the traditional categories of price dissemination, has also been referred to as customer relationship management based pricing (Shih and Sudhir, 2007), pricing with customer recognition (Esteves, 2010a, 2010b; Fudenberg and Tirole, 2000; Villas-Boas, 1999; Villas-Boas, 2004) or one-to-one pricing (Rossi et al., 1996; Shaffer and Zhang, 1997). Given the popularity of both practices, there have been several recent theoretical papers that attempted to understand the market conditions that determine when loyalty rewards are optimal and when poaching is optimal (e.g. Caminal and Clarici, 2007; Caminal and Matutes, 1990; Chen, 1997; Chen and Pearcy, 2010; Fudenberg and Tirole, 2000; Pazgal and Soberman, 2008; Villas-Boas, 1999; Shin and Sudhir, 2007, 2010).[2]

While the optimality of poaching or loyalty discounts depends on the assumptions of the specific model, generally poaching is found to be optimal. The general reasoning is that initial purchases help sellers identify the customers who value their product most and thus can be exploited later; that is the first period is used to segment the market. For example, Fudenberg and Tirole (2000)

[2] Based on the empirical analysis of Swedish newspaper subscriptions, Asplund, Eriksson and Strnad (2008) report that in competitive markets, the use of discounts to poach is inversely related to the seller's market share. There has also been work in monopoly settings considering pricing to new and repeat customers (e.g. Acquisti and Varian, 2005; Bikhchandani and McCardle, 2012; Villas-Boas, 2004).

use a simple two firm, two period Hotelling model where there is a continuum of relative brand preferences by customers. When customers' preferences do not change over time, the second period is essentially competition over two distinct markets, one for customers who prefer the seller and one for customers who prefer the rival. To capture the rival's customers, the seller must offer a low poaching price. However, Caminal and Matutes (1990) find that under the conditions of independent customer preferences and price pre-commitment for loyal customers, it can be more profitable for sellers to reward their own high-valued customers. Similar results are obtained by Shin and Sudhir (2007, 2010), who studied a market with high and low quantity demanded customers (see also Shaffer and Zhang, 2000).

In a recent paper, Chen and Pearcy (2010) develop a model that captures several key pieces of the behavior based pricing problem. They also consider a basic two period duopoly Hotelling model and show that the optimality of rewarding loyalty versus poaching depends on 1) the ability to pre-commit to future prices for repeat customers and 2) the degree to which buyer preferences vary between periods. In particular, Chen and Pearcy (2010) show that regardless of the ability to pre-commit to future prices, a lack of heterogeneity across time should lead to poaching. However, when there is heterogeneity in preferences over time and sellers can guarantee a future price to repeat buyers then loyalty is rewarded. The logic is that the low future price induces people to visit the seller initially and attract back those who may ultimately find themselves preferring the competitor in the future without having to offer low prices to those who do not visit initially but change to preferring that seller in the future. If there is sufficient heterogeneity and an inability to commit to future prices then the market essentially becomes a repeated single period Hotelling game as in Fudenberg and Tirole (2000).

While sellers routinely have to make the decision to poach or offer loyalty discounts, it can be difficult to study such markets empirically, because customer preferences and "distance costs" are inherently unobservable. Therefore, we turn to controlled laboratory experiments to empirically explore how the factors identified by Caminal and Matutes (1990), Chen and Pearcy (2010), and Fudenberg and Tirole (2000) among others impact behavior based pricing. Our paper reports the results of a series of market experiments, which vary the degree of heterogeneity in shopper preferences between periods and the ability of sellers to pre-commit to prices for loyal customers. Of course, naturally occurring markets have a myriad of other complicating factors such as more than two sellers being in operation, buyers making decisions over more than two periods, people entering and exiting the market asynchronously, etc. The goal in developing a theoretical model or an experiment is to focus on the interplay of the key elements. Thus controlled laboratory experiments are an ideal tool for cleanly examining seller reactions to factors the model has identified as strategically important.

Despite the recent theoretical work on behavior based pricing, the only related laboratory experiments of which we are aware are by Mahmood (2011) and Mahmood and Vulkan (2012), both of which are in the vein of Shin and Sudhir (2010) and in settings where loyalty discounts are not expected. Mahmood (2011) considers a discrete version of a high and low volume customer environment and allows for preference mobility.[3] Behaviorally, Mahmood (2011) does not observe loyalty discounts in any of the treatments and does observe poaching with customer recognition as anticipated. Mahmood and Vulkan (2012) conduct an experiment with professionals from a variety of industries. These experiments also involved high and low volume customers and varied the market structure (two firms on a Hotelling line or four firms on a Sallop circle) and the ability to price discriminate based on type. Their results suggest that greater competition reduces the magnitude of poaching and can encourage loyalty discounts.

The remainder of the paper is organized as follows. The next section lays out the theoretical framework for the markets examined in the lab. The experimental design and the experimental results are then presented in separate sections. A final section offers conducing remarks.

Market Structure

Our market structure follows that of Chen and Pearcy (2010). There are two firms $f \in [A, B]$ selling differentiated products a la a linear Hotelling model. For simplicity, we use the notation

[3] The environment is discrete in that there are only a few buyers who make purchase decisions rather than a continuum as in the theoretical model. This is due to the use of human subjects as buyers in those experiments. It is possible that equilibria differ between the continuous and discrete cases, but it is not clear which is more informative as to behavior in any particular naturally occurring market.

$-f$ to denote f's rival. Firms sell their products in two periods, n=1, 2. Customers demand one unit in the first period and one unit in the second period. Each period, customers are distributed uniformly over an interval of length $\bar{\theta}$. Firm A is located at 0 while Firm B is located at $\bar{\theta}$. In period n, a customer located at $\hat{\theta}$ receives a utility of v - p_A - $\hat{\theta}$ for purchasing from A at price p_A and receives a utility of v - p_B - ($\bar{\theta}$ - $\hat{\theta}$) from buying from B at price p_B. v is assumed to be sufficiently high that all buyers will purchase a unit in both periods. Total consumer cost in period n are denoted by C_n and include the price paid to a seller plus travel costs. In period 2, Firm f can identify customers who visited Firm f in period 1. Therefore, each firm sets three prices: P_1^f is Firm f's price in period 1, $\widetilde{P}_2^f$ is Firm f's price in period 2 for repeat (loyal) customers, and P_2^f is Firm f's price in period 2 for new customers. Sellers incur a constant marginal cost, c, for each unit sold.

With this basic framework, we consider the implications of two factors. The first is the relationship between buyer preferences in period 1 and period 2. Although Chen and Pearcy (2010) allow for a continuum of relationships, we focus on the two extreme cases: buyer preferences are independently determined each period and buyer preferences are fixed over time.[4] The second is the timing of when $\widetilde{P}_2^f$ is set: before or after buyers make their period 1 decisions. That is, whether or not sellers pre-commit to loyalty prices. Other prices are always set at the start of the period for which the price is in effect. The combinations of the two factors yield four distinct cases. A firm is said to poach if $\widetilde{P}_2^f > P_2^f$ and offer a loyalty discount if the inequality is reversed. Given the sequential nature of the market, the appropriate solution concept is that of subgame perfection. While Chen and Pearcy (2010) characterize the equilibrium, for our purposes it is also critical to identify the best response functions for both sellers in period 2 and buyers in period 1 in case observed first period seller behavior is off the equilibrium path. Buyers in period 2 will simply choose to purchase from the seller offering the lower total cost at that point.

[4] Chen and Pearcy (2010) model the preference relationship between periods using a copula with a continuous parameter α. Our cases correspond to theirs for α =0 and α =1.

Case 1: Independent Preferences and No Price Commitment

In this case, buyers are randomly relocated after the first period. Therefore, in period 2 the sellers are essentially competing on two independent Hotelling lines of length $\bar{\theta}$. The line for people who purchased from A in period 1 accounts for a fraction $\frac{\theta^*}{\bar{\theta}}$ of the total market and the remainder are uniformly distributed over the other line. Hence, the second period profit maximization problem for Firm A is to

$$\max_{\tilde{P}_2^A, P_2^A} \frac{\theta^*}{\bar{\theta}}\left(\tilde{P}_2^A - c\right)R + \left(1 - \frac{\theta^*}{\bar{\theta}}\right)\left(P_2^A - c\right)S$$

where *R* and *S* denote the location of the customers who did and did not visit Firm *A* in period 1, respectively, and who are now indifferent between the two firms in period 2 given the relevant period 2 prices. For concreteness,

$$R \equiv \frac{\bar{\theta} + P_2^B - \tilde{P}_2^A}{2} \qquad\qquad S \equiv \frac{\bar{\theta} + \tilde{P}_2^B - P_2^A}{2}$$

Firm *B* has a similar objective function. The first order conditions yield the following period 2 best response conditions:

$$P_2^f = \frac{\bar{\theta}}{2} + \frac{\tilde{P}_2^{-f}}{2} + \frac{c}{2} \text{ and } \tilde{P}_2^f = \frac{\bar{\theta}}{2} + \frac{P_2^{-f}}{2} + \frac{c}{2}.$$

From these conditions it is straight forward to show that in equilibrium

$$P_2^f = \tilde{P}_2^f = \mathrm{c} + \bar{\theta}. \tag{1}$$

In period 1, customers will decide where to shop based on the observed period 1 prices and the prices they expect to observe in period 2. θ^* can be identified by equating the expected utility of visiting Firm A in period 1 with the expected utility of visiting Firm B in period 1. That is θ^* is such that

$$v - P_1^A - \theta^* + \int_0^R (v - \theta - c - \bar{\theta})\frac{1}{\bar{\theta}}d\theta + \int_R^{\bar{\theta}} [v - (\bar{\theta} - \theta) - c - \bar{\theta}]\frac{1}{\bar{\theta}}d\theta =$$

$$v - P_1^B - (\bar{\theta} - \theta^*) + \int_0^S (v - \bar{\theta} - c - \theta)\frac{1}{\bar{\theta}}d\theta + \int_S^{\bar{\theta}} [v - \bar{\theta} - c - (\bar{\theta} - \theta^*)]\frac{1}{\bar{\theta}}d\theta,$$

which holds when $\theta^* = \frac{P_1^B - P_1^A}{2} + \frac{\bar{\theta}}{2}$. The integration arises due to the fact that in period 1, the customer does not know what her period 2 preferences will be. Given this, one can derive that the equilibrium first period prices are $P_1^A = P_1^B = c + \bar{\theta}$. In this case, firms do not reward loyalty or engage in poaching, making it an attractive baseline for comparing behavior across treatments.

Case 2: Constant Preferences and No Price Commitment

In this case, the buyers do not change their preferences between periods. Hence, in the second period the sellers will be competing over two non-overlapping markets, one consisting of buyers that are close to A and one consisting of buyers that are close to B. Each seller will end up setting high price in period 2 to those known to prefer it and low poaching prices to buyers who are known to prefer the rival.

Formally, the second period profit functions of the two firms are given by

$$\pi_2^A = \left(\widetilde{P}_2^A - c\right)R + (P_2^A - c)(S - \theta^*) \text{ and}$$

$$\pi_2^B = (P_2^B - c)(\theta^* - R) + \left(\widetilde{P}_2^B - c\right)(\bar{\theta} - S)$$

where R and S are defined as before. Simultaneously solving the four first order conditions yields the optimal second period prices:

$$P_2^A = \bar{\theta} + c - \frac{4}{3}\theta^* \qquad \widetilde{P}_2^A = \frac{\bar{\theta}}{3} + \frac{2}{3}\theta^* + c$$

$$P_2^B = \frac{4}{3}\theta^* + c - \frac{\bar{\theta}}{3} \qquad \widetilde{P}_2^B = \bar{\theta} + c - \frac{2}{3}\theta^*.$$

Therefore after observing the period 1 prices $\theta^*$is such that

$$v - \theta^* - P_1^A + v - (\bar{\theta} - \theta^*) - \frac{4}{3}\theta^* - c + \frac{\bar{\theta}}{3} =$$

$$v - (\bar{\theta} - \theta^*) - P_1^B + v - \theta^* - \bar{\theta} - c + \frac{4}{3}\theta^*,$$

which reduces to $\theta^* = \frac{3}{8}(P_1^B - P_1^A) + \frac{\bar{\theta}}{2}$. The optimal period 2 prices can thus be rewritten as

$$P_2^f = \frac{\bar{\theta}}{3} + c + \frac{P_1^f}{2} - \frac{P_1^{-f}}{2} \text{ and} \tag{2a}$$

$$\widetilde{P}_2^f = \frac{2\bar{\theta}}{3} + c - \frac{P_1^f}{4} + \frac{P_1^{-f}}{4}. \tag{2b}$$

It is straight forward to show that the equilibrium prices are given by $P_1^f = \frac{4\bar{\theta}}{3} + c$, $\widetilde{P}_2^f = \frac{2\bar{\theta}}{3} + c$, and $P_2^f = \frac{\bar{\theta}}{3} + c$, from which it is clear that new customers are being poached with a discount of $\widetilde{P}_2^f - P_2^f = \frac{\bar{\theta}}{3}$. A second interesting feature of the equilibrium is that all second period prices should be less than first period prices.

The above analysis applies so long as $P_2^A, \widetilde{P}_2^A, P_2^B, \widetilde{P}_2^B \geq c$, which holds for $\theta^* \in \left[\frac{\bar{\theta}}{4}, \frac{3\bar{\theta}}{4}\right]$. When $\theta^* < \frac{\bar{\theta}}{4}$, firm 2 will only push its price for new customers down to cost, i.e. $P_2^B = c$, to which firm 1 will respond by setting $\widetilde{P}_2^A = \bar{\theta} - 2\theta^* + c$. Similarly, when $\theta^* > \frac{\bar{\theta}}{4}$ then $P_2^A = c$ and $\widetilde{P}_2^B = 2\theta^* - \bar{\theta} + c$.[5]

Case 3: *Independent Preferences with Price Commitment*

In this case, sellers will be competing over two independent lines in period 2, but they will have already set their price for the line involving their repeat customers. Thus there is only one choice variable for a firm in period 2, the price to charge new customers, which can be a function of the rival's price to repeat customers. The somewhat surprising result is that in this case sellers offer lower prices to their repeat customers. The intuition is that a seller wants to guarantee a low repeat price so as to attract customers in period 1, but in period 2 the seller finds it better to exploit the new customers who are close by, rather than trying to compete with the rival's low loyalty price.

With independent preferences and repeat price commitment, the second period profit functions for A and B are

$$\pi_2^A = \left(\widetilde{P}_2^A - c\right)\frac{\theta^*}{\bar{\theta}}R + (P_2^A - c)S\left(1 - \frac{\theta^*}{\bar{\theta}}\right) \text{ and}$$

$$\pi_2^B = \frac{\theta^*}{\bar{\theta}}(\bar{\theta} - R)(P_2^B - c) + \left(1 - \frac{\theta^*}{\bar{\theta}}\right)\left(\widetilde{P}_2^B - c\right)(\bar{\theta} - S).$$

The resulting optimal prices for new customers in period 2 are given by:

$$P_2^f = \frac{\bar{\theta}}{2} + \frac{c}{2} + \frac{\widetilde{P}_2^{-f}}{2}. \tag{3}$$

As in Case 1, θ^* is determined taking into account that the buyers do not know what their preferences will be in period 2. The solution that

$$\theta^* = \frac{(P_1^B - P_1^A)}{2} + \frac{\bar{\theta}}{2} + \frac{\left(\widetilde{P}_2^B - \widetilde{P}_2^A\right)}{2}\left(\frac{7}{8} + \frac{c}{8\bar{\theta}}\right) + \frac{\left(\widetilde{P}_2^A\right)^2 - \left(\widetilde{P}_2^B\right)^2}{32\bar{\theta}}$$

comes from equating

$$v - \theta^* - P_1^A + \int_0^R\left[v - \theta - \widetilde{P}_2^A\right]\frac{1}{\bar{\theta}}d\theta + \int_R^{\bar{\theta}}\left[v - (\bar{\theta} - \theta) - P_2^B\right]\frac{1}{\bar{\theta}}d\theta \text{ with}$$

[5] Empirically, there was a single instance for which $\theta^* \notin \left[\frac{\bar{\theta}}{4}, \frac{3\bar{\theta}}{4}\right]$ in the experimental investigation of this case.

$$v - P_1^B - (\bar{\theta} - \theta^*) + \int_0^S (v - P_2^A - \theta)\frac{1}{\bar{\theta}}d\theta + \int_S^{\bar{\theta}} \left[v - \widetilde{P}\,_2^B - (\bar{\theta} - \theta)\right]\frac{1}{\bar{\theta}}d\theta.$$

Sellers of course take into account how their period 1 choices of P_1^f and $\widetilde{P}\,_2^f$ affect θ^*. The resulting subgame perfect equilibrium prices are $P_1^f = \frac{4\bar{\theta}}{3} + c$, $\widetilde{P}\,_2^f = -\frac{\bar{\theta}}{3} + c$, and $P_2^f = \frac{\bar{\theta}}{3} + c$. The loyalty discount is the difference between $P_2^f - \widetilde{P}\,_2^f$ and equals $\frac{2}{3}\bar{\theta}$. It is also interesting to note that the first period price and the second period price for new customers should be the same in Cases 2 and 3. The only change in equilibrium behavior is the price charged to loyal customers, which should now be *below* cost. Also as in Case 2, all period 2 prices are below those in period 1.

Case 4: Constant Preferences with Price Commitment

Like Case 2, the sellers are competing over two distinct regions, but as in Case 3, each firm has a single choice variable in period 2. Therefore, the second period profit functions are simpler than those of Case 2. Specifically:

$$\pi_2^A = \left(\widetilde{P}\,_2^A - c\right)R + (P_2^A - c)(S - \theta^*)$$
$$\pi_2^B = (P_2^B - c)(\theta^* - R) + \left(\widetilde{P}\,_2^B - c\right)(\bar{\theta} - S)$$

The first order conditions give:

$$P_2^A = \frac{\bar{\theta} + \widetilde{P}\,_2^B + c}{2} - \theta^* \qquad\qquad P_2^B = \frac{-\bar{\theta} + \widetilde{P}\,_2^A + c}{2} + \theta^*.$$

As buyer preferences do not change, θ^*can be found by setting

$$v - \theta^* - P_1^A + v - (\bar{\theta} - \theta^*) - \theta^* + \frac{\bar{\theta}}{2} - \frac{\widetilde{P}\,_2^A}{2} - \frac{c}{2} =$$
$$v - (\bar{\theta} - \theta^*) - P_1^B + v - \theta^* + \theta^* - \frac{\bar{\theta}}{2} - \frac{\widetilde{P}\,_2^B}{2} - \frac{c}{2},$$

which yields $\theta^* = \frac{(P_1^B - P_1^A)}{2} + \frac{\bar{\theta}}{2} + \frac{(\widetilde{P}\,_2^B - \widetilde{P}\,_2^A)}{4}$. Therefore, the period 2 best responses can be written as

$$P_2^f = \frac{c}{2} + \frac{P_1^f}{2} - \frac{P_1^{-f}}{2} + \frac{\widetilde{P}\,_2^f}{4} + \frac{\widetilde{P}\,_2^{-f}}{4}. \tag{4}$$

As a result, equilibrium prices are $P_1^f = \bar{\theta} + c$, $\widetilde{P}_2^f = \frac{\bar{\theta}}{2} + c$, and $P_2^f = \frac{\bar{\theta}}{4} + c$. Here new customers receive a discount of $\frac{\bar{\theta}}{4}$ and as in Cases 2 and 3 all second period prices are expected to be below first period prices.

Experimental Design

To explore BBP, we conducted a series of controlled laboratory experiments using a 2 × 2 design. Corresponding to the four cases modeled in the previous section, the first dimension was the relationship of preferences between periods (fixed or independent) and the second dimension was the ability to pre-commit to the price charged to repeat customers (not possible or possible). The parameters preferences used in the experiment were $\bar{\theta}$ = 120 and c = 50. While these parameters are somewhat arbitrary, they lead to clear separation in predicted prices. The resulting price predictions are summarized in Table 1.

Table 1. Price Predictions

Case	1-Baseline	2	3	4
Buyer Preferences	Independent	Fixed	Independent	Fixed
Price Pre-commitment	No	No	Yes	Yes
P_1^f	170	210	210	170
$\widetilde{P}_2^f$	170	130	10	110
P_2^f	170	90	90	80
π^f	14 400	13 600	8 000	12 750
C	48 000	47 200	36 800	40 350

In order to aide subject comprehension, the task was presented to subjects as a problem faced by a pair of ice cream vendors located at opposite end of a beach on a crowded day. Each "day" in the experiment a subject could set a morning price for everyone and separate afternoon prices for repeat and new customers. As explained to the subjects, all of the buyers in the market were computerized robots who determined their decisions based only on price and travel distance and behaved optimally given the observed prices (that is θ^*, R, and S followed the derivations in the previous section). For simplicity, each subject was presented the task as though she was firm A located at 0 and their rival was firm B located at $\bar{\theta}$ =120. Figure 1 shows a sample image of the subject screen in the baseline case.

Figure 1: Subject Decision Screen in Baseline Case

A session consisted of four subjects. To eliminate repeated play incentives, each "day" subjects were randomly and anonymously rematched with someone else in their session. Treatment effects are evaluated between subjects as each session involved only a single treatment case. After entering the lab, subjects read printed instructions and completed a comprehension handout (both available in the Appendix). Once everyone had completed the handout the experiment began. The experiment lasted 20 "days" and the subjects were paid their cumulative earnings, which were converted from the lab dollars used in the experiment to cash at the rate of 2500 Lab Dollars = US$0.10. Subjects did not know in advance how many "days" the experiment would last, but did know the exchange rate.

The experiments were conducted in The Behavioral Business Research Laboratory at the University of Arkansas. Multiple sessions in different treatments were conducted concurrently so as to eliminate the effect of any uncontrolled nuisance variables and to further mask the identity of one's rival in any given period. The participants were drawn from the lab's participant database, which is comprised primarily of undergraduate students. None of the subjects had participated in any related studies although some had participated in other unrelated experiments. As is standard in the lab, subjects were paid a $5 participation payment for the approximately one hour experiment in addition to their salient earnings, which averaged $16.25.

Experimental Results

The data consist of 3840 market pricing decisions from 16 sessions (four replications of each of the four treatments).[6] Aggregate behavior is displayed graphically in Figure 2 and summarized in Table 2.

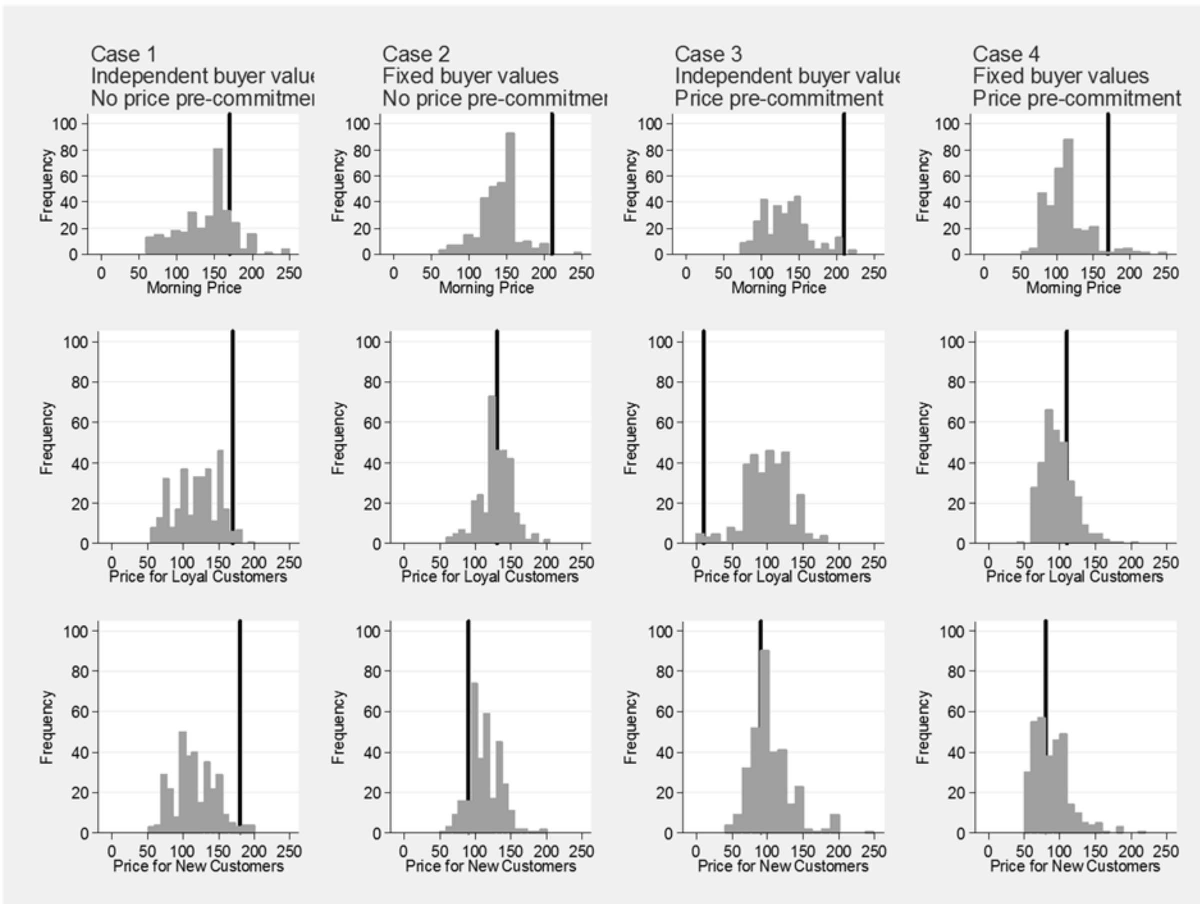
In the baseline case 1, where consumer preferences are independent over time and there is no price pre-commitment, the price should be 170 in every situation. Figure 1 and Table 2 clearly show that prices are lower than predicted. Where a buyer purchased in period 1 should have no effect on prices in period 2, a result affirmed in Table 2 by the lack of significance for the Loyal Customer Price Effect in column 1. However, prices should be the same in the afternoon and the morning, a result which does not hold as afternoon prices are significantly lower as evidenced by the significance of the Afternoon Price Effect in column 1.

In cases 2 and 4, where buyer preferences are fixed, the prediction is that afternoon prices are lower than morning prices and that sellers engage in poaching. The regression results in Table 2 indicate that both patterns hold, significantly for Case 2 and at least nominally for Case 4. However, in neither case the size of the loyalty discount is as large as it should be. The reason for this differs between the two cases. In case 2, prices to new customers are not as low as they

[6] The analysis of data was done on the whole dataset. The results remain qualitatively unchanged if the first ten "days" are dropped.

should be whereas in case 4, prices to loyal customers are not as high as they should be. For both cases morning prices are lower than the predicted value.

Figure 2: Distribution of Prices



Note: Solid line represents prices predicted by model.

We now turn to case 3, where sellers are predicted to offer discounts to loyal customers because buyer preferences vary over time and price pre-commit is available. As in the other cases, morning prices are significantly too low (see Table 2). While sellers are offering nominally higher prices to new customers, the difference is not statistically significant. The main driving factor is that sellers are generally unwilling to commit to pricing *below* cost as required by the model. From Figure 1, it is clear that although some sellers in this setting do price below cost, the vast majority price above cost. Still, in the other three cases sellers essentially never price below cost and rarely price close to cost. One possible explanation is that subjects exhibit loss aversion. In addition, as shown in Table 1 this practice actually leads to much lower profits for the sellers so they have an incentive to avoid it. Alternatively, subjects may consider pricing below cost as socially inappropriate "predatory pricing" or an unfair trade practice (e.g. Bolton, Brodley and Riordan, 2000; Petit and Neyrinck, 2010).

Table 2: Analysis of Prices by Case

Case	1-Baseline	2	3	4
Buyer Preferences	Independent	Fixed	Independent	Fixed
Price Pre-commitment	No	No	Yes	Yes
Morning Price P_1^f				
Mean	141.5	138.2	133.3	112.2
Model	170	210	210	170
p-value	0.002	<0.001	<0.001	<0.001
Price for Loyal Customers $\widetilde{P}_2^f$				
Mean	119.7	129.2	99.6	94.6
Model	170	130	10	110
p-value	<0.001	0.750	<0.001	0.006
Price for New Customers P_2^f				
Mean	116.5	114.1	104.5	86.8
Model	170	90	90	80
p-value	<0.001	<0.001	0.043	0.353
Regression Results for Comparing Prices Within a Day				
Afternoon Price Effect	-25.028**	-24.041***	-28.800**	-25.412**
	(7.227)	(3.094)	(8.735)	(5.881)
Loyal Customer Price Effect	3.250	15.022**	-4.919	7.753
	(7.889)	(3.857)	(6.749)	(4.933)
Constant	141.512***	138.172***	133.319***	112.213***
	(9.363)	(1.306)	(13.114)	(6.581)
Observations	960	960	960	960

Note: The afternoon price effect is the incremental change from morning prices that applies to both $\widetilde{P}_2^f$ and P_2^f whereas the Loyal Customer Price Effect is the incremental effect for $\widetilde{P}_2^f$ relative to P_2^f. Clustered standard error in parentheses. ** and *** denote significance at the 5% and 1% level, respectively. For Cases 2, 3, and 4 with directional predictions for the size of the loyalty discount, the appropriate 1-sided hypothesis is implemented.

At first pass, the reluctance of sellers to price below cost appears to call into question the predictive success of the model for identifying when loyalty discounts will be observed. However, further analysis reported in Table 3 shows that the intuition provided by the model does correspond to observed behavior in that sellers were significantly more likely to offer loyalty discounts in case 3. Specifically, Table 3, reports the results of a probit regression where the dependent variable equals one if the seller offered any loyalty discount in a given day and is zero if the seller engaged in poaching (or offered the same price to both groups). The estimation in Table 3 includes case specific dummy variables. In addition to demonstrating that loyalty discounts are more prevalent in case 3 as evidence by the positive and significant coefficient, Table 3 also clearly indicates that poaching is more common in cases 2 and 4 exactly as predicted. Together these results indicate a reasonable degree of success for the model in terms of when poaching is likely to occur even if the magnitude is not as great as expected.

Table 3: Analysis of Sellers' Willingness to Offer Loyalty Discount by Case

Variables	**Constant**	**Case 2**	**Case 3**	**Case 4**
Coefficient	-0.311***	-0.541***	0.489**	-0.250***
	(0.114)	(0.106)	(0.109)	(0.076)
p-value	<0.001	<0.001	0.021	<0.001

Note: Dependent variable is binary and equals to 1 if loyalty is present and 0 if not, we did not take into account situation where sellers offered the same price for new and repeated customers. Analysis is done on individual decision level. Robust standard errors are in parentheses. ** and *** denote significance at the 5% and 1% level, respectively.

All of the preceding analysis examines unconditional behavior. However, as shown in equations (1)-(4), prices set in the afternoon should depend on prices set in the morning, except in the baseline. From (3), for case 3 $\frac{\partial P_2^f}{\partial \tilde{P}_2^{-f}} = \frac{1}{2}$, so that as the rival's price to loyal customers increases, one's own price to new customers should increase by a smaller amount. This means that the optimal loyalty discount is shrinking as overall afternoon price levels increase. Thus, reluctance by sellers to price below cost would lead to smaller loyalty discounts, exactly the pattern that we observe. To explore this in more detail, we conducted regression analysis of afternoon prices as a function of the prices set in the morning as appropriate for each case. The results are shown in Table 4.

In addition to showing that new customer prices increase less than one to one with the rival's loyalty price, the results for case 3 in Table 4 indicate that people who set high prices for loyal customers also set high prices for new afternoon customers even though their own loyalty price should not matter. Subjects also appear to falsely believe that rivals who set high morning prices

Table 4: Afternoon Pricing Behavior as a Function of Prices Set in the Morning

Case	1-Baseline		2		3	4
Buyer Preferences	Independent		Fixed		Independent	Fixed
Price Pre-commitment	No		No		Yes	Yes
Estimated Equation	P_2^f from (1)	$\tilde{P}_2^f$ from (1)	P_2^f from (2a)	$\tilde{P}_2^f$ from (2b)	P_2^f from (3)	P_2^f from (4)
Constant						
Predicted	170	170	90	130	85	25
Observed	61.517***	47.860**	30.158	13.287***	22.635***	15.652
	(18.714)	(19.022)	(21.335)	(2.394)	(4.445)	(14.939)
p-value	<0.001	<0.001	0.0050	<0.001	<0.001	0.5315
P_1^f						
Predicted	0	0	0.5	-0.25	0	0.5
Observed	0.157***	0.270**	0.334***	0.601***	0.177	0.072
	(0.053)	(0.108)	(0.072)	(0.029)	(0.149)	(0.075)
p-value	0.0029	0.0122	0.0207	<0.001	0.2341	<0.001
P_1^{-f}						
Predicted	0	0	-0.5	0.25	0	-0.5
Observed	0.232***	0.238***	0.273***	0.238***	0.152*	0.107
	(0.041)	(0.031)	(0.096)	(0.042)	(0.078)	(0.066)
p-value	<0.001	<0.001	<0.001	0.7676	0.0509	<0.001
$\tilde{P}_2^f$						
Predicted	-	-	-	-	0	0.25
Observed					0.207**	0.338***
					(0.094)	(0.063)
p-value					0.0276	0.1674
$\tilde{P}_2^{-f}$						
Predicted	-	-	-	-	.5	0.25
Observed					0.175***	0.203***
					(0.035)	(0.028)
p-value					<0.001	0.0906

Note: Standard errors clustered at the session level are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. P-values are for testing the null hypothesis that the observed behavior is equal to the predicted value against the two sided null hypotheses.

are likely to set high afternoon prices for new customers and respond with higher prices. This belief is also found in the other cases as well, although it is justified in cases 1 and 2 as a higher morning price does lead to higher afternoon prices. For case 2, this can explain why subjects are raising their prices when they should be lowering them. Although a higher morning price by one's rival pushes θ^* away and thus calls for a lower price than in equilibrium, this predicted response is assuming that the rival will behave optimally in stage 2. If a rival that charges too high a price in the morning will also charge too high of a price in the afternoon then it makes sense not to lower one's own price relative to the equilibrium.

We return to session level analysis to ask how the treatment variables impact price levels. To do this, we estimate $\mathcal{P}_{it} = \beta_1 + \beta_2\, Stability + \beta_3 Precommitment + \varepsilon_{it}$, where $\mathcal{P}$ is a price; $i \in (1, 64)$ is a subject; $t \in (1, 20)$ is a day; $\varepsilon_{it} \sim N\ (0, \sigma_k^2)$ and $k \in (1,16)$ is a session. $Stability$ is an indicator variable that takes the value 1 if the observation is from a session where buyer preferences are stable and is 0 otherwise. $Precommitment$ is an indicator variable that takes the value 1 if the observation is from a session where price pre-commitment is possible and is 0 otherwise. The regression results are presented in Table 5 with standard errors clustered at the session level. Based on the evidence in Table 5, it appears that price levels are driven by the ability to pre-commit to prices for loyal customers and not the variability in customer preferences. Specifically, the ability to pre-commit leads to lower prices in the morning, lower prices for new customers in the afternoon and for loyal customers in the afternoon.

Table 5: Impact of Market Characteristics on Prices, Sellers Profit and Total Consumer Costs

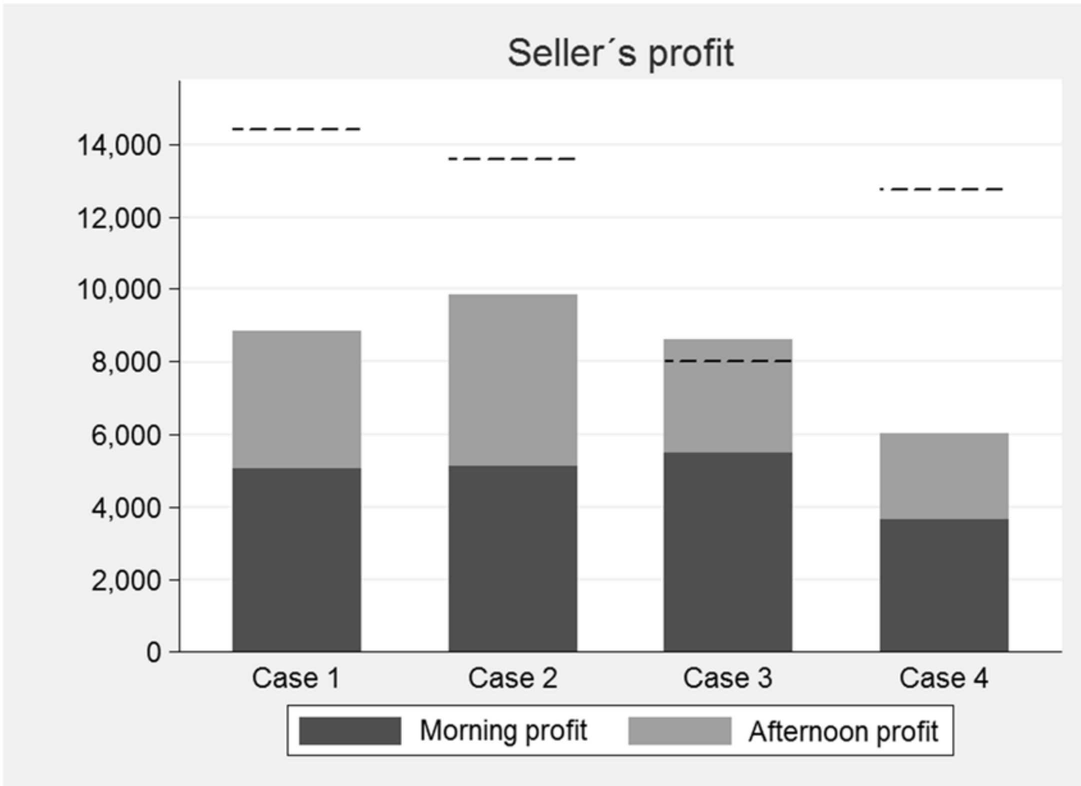
	Morning Price	**Price for Loyal Customers**	**Price for New Customers**	**Sellers Profit**	**Total Consumer Costs**
Preference Stability	-12.223 (8.134)	2.186 (7.691)	-10.036 (6.951)	-317.9196 (946.083)	-1139.76 (0.507)
Price Commitment	-17.077** (8.134)	-27.367*** (7.691)	-19.648*** (6.951)	-2475.61** (932.170)	-4451.95** (0.009)
Constant	145.954*** (7.364)	123.351*** (9.47)	120.326*** (7.511)	9497.779*** (883.226)	38619.31*** (<0.001)
Observations	1280	1280	1280	1280	640

Note: Standard error in parentheses. ** and *** denote significance at the 5% and 1% level, respectively.

Table 5 also reports how the treatment variables impact seller profits and consumer costs. It is important to note that profit and costs do not need to move with prices since customers experience incur travel costs and prices affect market share. The results in Table 5 reveal that pre-commitment significantly lowers seller profit and it is also detrimental to shoppers. The later result is intuitive in that sellers can exploit the better information about shoppers in the afternoon when preferences are fixed, while the former result is less intuitive but driven by the overall lower price level.

Figure 3 shows morning and afternoon profit for each case. Across all conditions, a majority of seller profit is achieved in the morning. Without price pre-commitment, sellers are able to extract relatively large afternoon profits when they know the preferences of shoppers. The figure also shows that the lower profits with price pre-commitment are driven by reductions in afternoon profits, when both repeat and new customer prices are low. Further, the lost profit from the competitive pressure of pre-commitment more than offsets the benefit of knowing the preferences of shoppers.

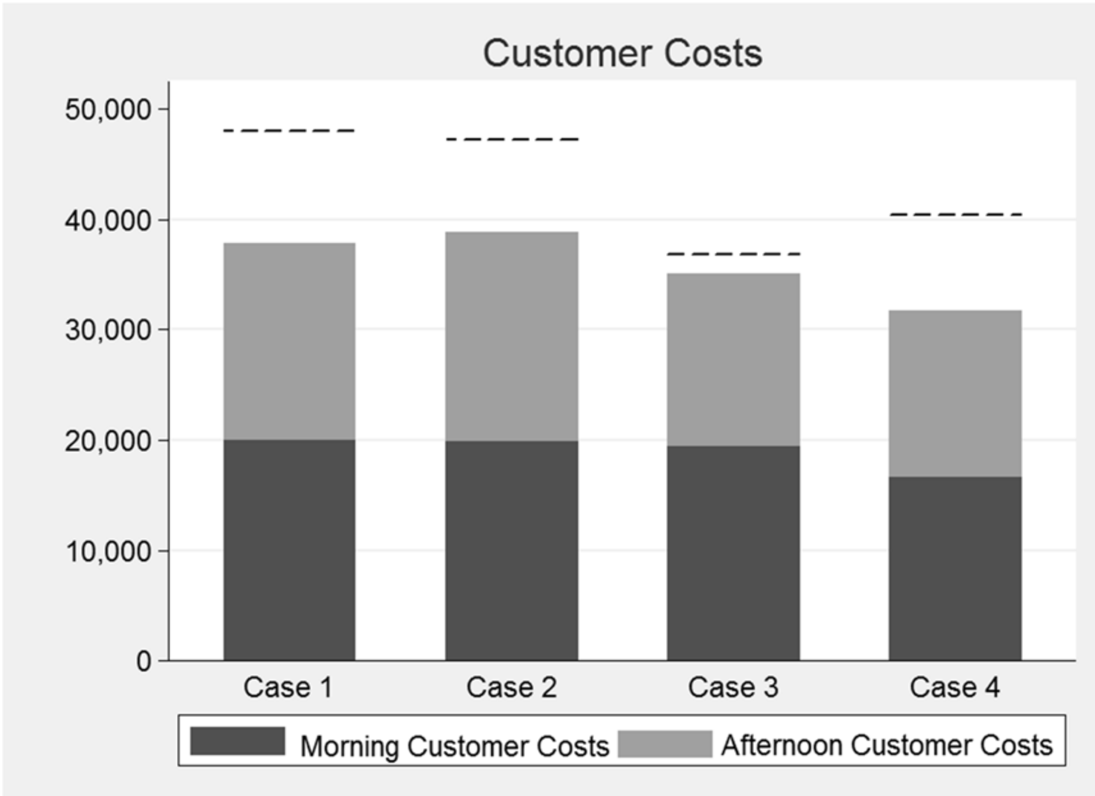
Figure 3: Comparison of Morning and Afternoon Profit (means) by Case



Note: Dash lines represent values predicted by the model.

Figure 4 plots consumer costs in the morning and the afternoon for each case. The figure clearly shows that in total cost to consumers in the morning is similar in cases 1, 2, and 3, but is lower in case 4. The graph also shows that afternoon consumer costs are lower when sellers have price pre-commitment (cases 3 and 4) then when sellers cannot (cases 1 and 2). However, the stability of consumer preferences has the opposite impact from what was expected. In cases without price pre-commitment (cases 1 and 2), fixed consumer preferences increase total consumer costs in the afternoon, while in cases where sellers can engage in price pre-commit for repeated buyers (cases 3 and 4) total consumer costs increase when buyer preferences are not fixed.

Figure 4: Comparison of Morning and Afternoon Total Customer Costs (means) by Case



Note: Dash lines represent values predicted by the model.

Finally, we compare how similar observed profits and total consumer costs are to their predicted levels for each treatment. To do this, we conduct the following analysis: $D_{it} = \beta_1 + \beta_2\, Case_2 + \beta_3 Case_3 + \beta_4\, Case_4 + \varepsilon_{it}$, where D denotes the difference between the observed and predicted level of the specific welfare measure where $Case_j$ is an indicator variable that takes the value 1 if the observation is from Case j and is 0 otherwise. The results, show in Table 6, indicate that for three of the cases seller profits and total consumer costs are well below the predicted levels. However, in Case 3 profits and consumer costs are similar to the predicted levels. In Cases 1, 2, and 4 sellers are observed to be engaging in strong competition, which is pushing prices down harming profits to the benefit of consumers. However, when shopper preferences are not fixed and price pre-commitment is possible sellers are unwilling to price below costs and fully exploit loyalty pricing. This has the effect of weakening competitive pressure and increasing profits in exactly the case where profits were predicted to be the lowest.

Table 6: Comparison of Observed and Predicted Welfare Measures

Analysis of Seller Profit				
Regression	-5556.414^{***}	1790.467^{*}	6149.79^{***}	-1143.53
p-value for Ho: $\beta_i=0$	<0.001	0.087	<0.001	0.373
Test Observed = Predicted	Case 1	Case 2	Case 3	Case 4
Ho:	$\beta_1=0$	$\beta_1+\beta_2=0$	$\beta_1+\beta_3=0$	$\beta_1+\beta_4=0$
p-value	<0.001	<0.001	0.6836	<0.001
Analysis of Total Consumer Cost				
Regression	-10118.79^{***}	1735.719	8347.253^{**}	1471.409
p-value for Ho: $\beta_i=0$	<0.001	0.451	0.003	0.565
Test Observed = Predicted	Case 1	Case 2	Case 3	Case 4
Ho:	$\beta_1=0$	$\beta_1+\beta_2=0$	$\beta_1+\beta_3=0$	$\beta_1+\beta_4=0$
p-value	<0.001	<0.001	0.2887	<0.001

Note: Dependent variable is Observed Value – Predicted Value. Analysis is done at the individual level for profit and at the market level for consumer cost. Robust standard errors are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Conclusions

This paper reports an experimental investigation of behavior based pricing for competing duopolists who can charge different prices to buyers with different purchase histories. The setting closely follows the theoretical model developed by Chen and Pearcy (2010) in considering the effect of changes in buyer preferences and the ability of sellers to pre-commit to prices for repeat buyers when the sellers offer differentiated products to a continuum of shoppers. Specifically, we conducted a series of controlled laboratory experiments varying these two factors resulting in four distinct market cases. In the markets, seller set three different prices – a morning price, an afternoon price for loyal customers and an afternoon price to poach customers who visited the rival seller in the morning.

The results of our experimental study generally support the comparative static results of the theoretical model, although the point predictions typically do not. In general, there is less difference between prices in different treatments than predicted. Morning prices are higher than afternoon prices as predicted in most cases, although morning prices are also higher in the baseline where this change is not predicted. When buyer preferences are not stable over time and sellers cannot make price pre-commitments, sellers should not differentiate between new and repeat customers and on average they do not. Fixing customer preferences over time should lead to seller's exploiting repeat customers and poaching new customers from rivals and this is what we observe. Allowing price pre-commitment for repeat shoppers when buyer preferences are independent over time should lead to loyalty discounts being offered. Loyalty discounts are more likely to be observed in this case, but the size of the discounts does not match the theoretical prediction. This appears to be due in part to the fact that the predicted loyalty discounts actually involve pricing below cost, something the subject sellers were reluctant to do although it is far more common in this case than in any of the others. The results also indicate that subject sellers are basing their prices on information that is not relevant in equilibrium. However, if out of equilibrium behavior is taken as a signal of future pricing then this response could be optimal. For example, if one believes that a seller who sets a relatively high price in the morning will also overprice later in the day, then increasing one's own afternoon prices could be reasonable. Another interesting finding is that the ability to pre-commit to prices has a greater impact on price levels than the intertemporal relationship among buyer preferences. In particular, the use of price pre-commitments lead to lower prices and thus lower profits for seller indicating that the practice may be something seller want to avoid.

As technology continues to enable more tailored pricing and shopping experiences in general, it is increasingly important to understand how practices such as behavior based pricing will impact market outcomes. While there has been some work on this issue form a theoretical perspective, there has been relatively little empirical study. In part this may be driven by important aspects of the problem, such as the stability of buyer preferences, being unobservable in the field. We use the laboratory to overcome this problem and believe this is a fruitful avenue for investigating behavior based pricing. This is not to argue that lab experiments should be viewed as a substitute for field work. Rather, the two approaches are complements as laboratory studies necessarily reduce the complexity and richness of the decision problem. One specific aspect of the behavior based pricing practice that we believe merits future investigation is in identifying how buyers react to the differential pricing. Our results are based on the assumption that buyers are both forward looking and profit maximizing. Such assumptions are appropriate when evaluating theoretical models where this assumption is maintained as was our goal. However, the assumption that buyers will maximize their profits when making a second purchase and thus truthfully reveal their preferences at that point may or may not be valid. It might be a reasonable assumption when buyers have little market power, but it is easy to imagine a returning customer becoming upset about being charged more than a new customer and as result switch sellers even if it means paying more.

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Appendix A. Subject Directions and Comprehension Handout

[Text in brackets was not observed by the subjects.]

Experiment Instructions

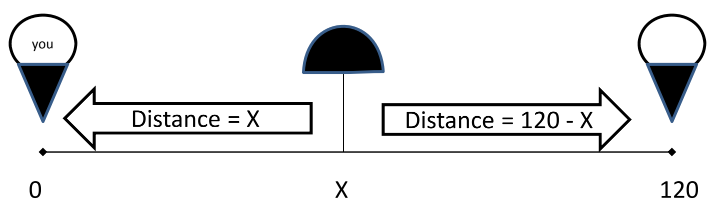
In this experiment, you will be paid based in part upon your decisions. Therefore, it is important that you understand the instructions completely. If you have any questions, please raise your hand and someone will come to your desk.

What am I doing in this Experiment? You are a seller.

In today's experiment you will be in the role of a seller. You can think of yourself as running an ice cream shop at a beach that is 120 yards long. Your shop is located at one end of the beach. Someone else is running an ice cream shop at the other end of the beach. Every "day" new people come to visit the beach and sit under their umbrellas, which are located evenly and continuously all along the length of the beach.

Everyone at the beach wants to buy ice cream twice, once in the morning and once in the afternoon. You and the other seller will each set your own price for ice cream. When deciding where to buy their ice cream, the people on the beach look at both the price that is being charged and the distance in yards they have to travel to reach the shop.

Cost to Customer = Price + Distance to Shop



For example, suppose you set a price of 140 and the other seller set a price of 160

A customer located at X = 50 yards from you and hence 70 = 120 – 50 yards from the other seller

would incur a cost of 190 = 140 + 50 to buy from you.

would incur a cost of 230 = 160 + 70 to buy from the other seller.

A customer located X= 80 yards from you and hence 40 = 120 – 80 yards from the other seller

would incur a cost of 220 = 140 + 80 to buy from you.

would incur a cost of 200 = 160 + 40 to buy from the other seller.

[CASE 1]

At the start of the day you and the other seller will each set your morning price.

While the people at the beach go to lunch, you can set your afternoon prices. You can set different prices for people who bought ice cream from you in the morning and for people who bought ice cream from the other seller in the morning. The other seller also sets afternoon prices for repeat customers and for new customers who bought ice cream from you in the morning.

After lunch people randomly choose a new location on the beach so where they were in the morning does not tell you anything about where they will be in the afternoon.

[CASE 2]

At the start of the day you and the other seller will each set your morning price.

While the people at the beach go to lunch, you can set your afternoon prices. You can set different prices for people who bought ice cream from you in the morning and for people who bought ice cream from the other seller in the morning. The other seller also sets afternoon prices for repeat customers and for new customers who bought ice cream from you in the morning.

After lunch people come back to the exact same place on the beach they were before lunch.

[CASE 3]

At the start of the day you and the other seller will each set your morning price. At the start of the day you and the other seller will also set your price for a second serving, the price at which a repeat customer can come back in the afternoon and pay for ice cream.

While the people at the beach go to lunch, you can set your price for customers who did not buy ice cream from you in the morning (that is your price for the people who bought ice cream from the other seller in the morning). The price that you charge these new customers can be more than, less than or equal to the price you charge repeat customers. The other seller also sets an afternoon price for new customers that bought ice cream from you in the morning.

After lunch people randomly choose a new location on the beach, so where they were in the morning does not tell you anything about where they will be in the afternoon.

[CASE 4]

At the start of the day you and the other seller will each set your morning price. At the start of the day you and the other seller will also set your price for a second serving, the price at which a repeat customer can come back in the afternoon and pay for ice cream.

While the people at the beach go to lunch, you can set your afternoon price for customers who did not buy ice cream from you in the morning (that is your price for the people who bought ice cream from the other seller in the morning). The price that you charge these new customers can be more than, less than or equal to the price you charge repeat customers. The other seller also sets an afternoon price for new customers that bought ice cream from you in the morning.

After lunch people come back to the exact same place on the beach they were before lunch.

[END CASES]

If I am selling, who is buying? Buyers are automated by the computer.

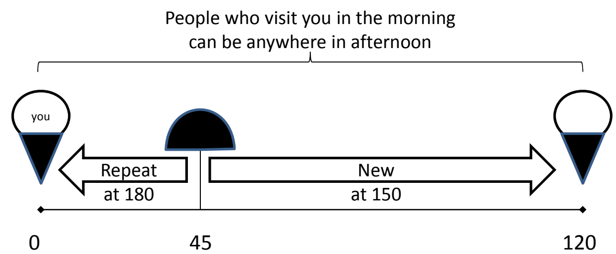
In the afternoon, the computerized buyers simply look at the prices (the repeat customer price of the seller visited in the morning and new customer price of the seller not visited) and purchase from whichever seller offers the best deal (lowest sum of price + distance).

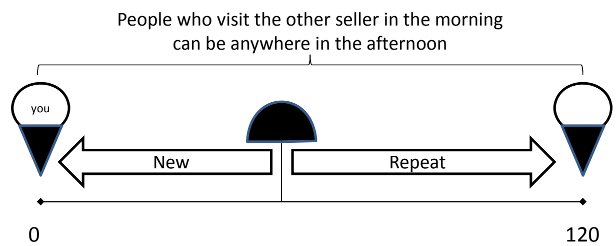
For those who bought from you in the morning, based on your price for a repeat customer and the other seller's price for new customers, there will be a cutoff point on the beach and everyone who bought from you in the morning and is now closer to you than that cutoff will buy ice cream from you at your repeat customer price. The rest will buy from the other seller. Similarly, for those who bought from the other seller in the morning, based on your price for a new customer and the other seller's price for a repeat customer, there will be a cutoff point on the beach and everyone who bought from the other seller in the morning and is now closer to you than that cutoff will buy ice cream from you at your new customer price. The rest will buy from the other seller.

In the morning, the computerized buyers look at the current prices, their current location, and what they anticipate will happen in the afternoon. The buyers anticipate that both sellers will choose prices optimally in the afternoon given what happens in the morning. Computerized buyers then determine where to go in the morning so as to minimize their expected total cost for their morning plus afternoon purchases. This does not mean that buyers will visit the same seller in the morning and the afternoon. Depending on the prices and their locations different buyers may anticipate visiting the same seller twice or each seller once. Again, the result of this buyer behavior is that there will be a cutoff point on the beach in the morning based upon the prices that have been set. Everyone closer to you than this cutoff point will buy from you at your morning price. Everyone further away than this point will buy from the other seller in the morning.

[CASES 1 & 3]

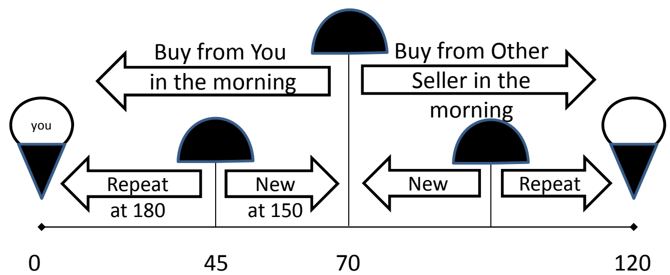
For example, suppose that in the morning, everyone up to the cutoff of 70 comes to your shop. If you set a price of 180 for repeat customers and the other shop set a price of 150 for new customers, then in the afternoon a person located at 45 who had come to you in the morning would have a cost of 225 (price + distance) from each seller. Everyone who visited you in the morning and was now located closer to you than 45 would come to you as a repeat customer in the afternoon. Everyone now located between 45 and 120 who had visited you in the morning would visit the other seller as a new customer in the afternoon. People that were further away from you than 70 in the morning visited the other seller in the morning and thus would be comparing your new customer price and the other seller's repeat customer price and there would be some cutoff for those people as well.





[CASES 2 & 4]

For example, suppose that in the morning, everyone up to the cutoff of 70 comes to your shop. If you set a price of 180 for repeat customers and the other shop set a price of 150 for new customers, then in the afternoon a person located at 45 would have a cost of 225 (price + distance) from each seller. Everyone located closer to you than 45 would come to you as a repeat customer in the afternoon. Everyone located between 45 and 70 would visit the other seller as a new customer in the afternoon. People that are further away from you than 70 visited the other seller in the morning and thus would be comparing your new customer price and the other seller's repeat customer price and there would be some cutoff for those people as well.



[End CASES]

The right hand portion of your screen will show you what happens each day. There will be three bars representing the beach: a morning bar, an afternoon bar for those that visited you in the morning, and an afternoon bar for those that visited the other seller in the morning. The bars will be color coded with your prices and customer locations in green and the other seller's prices and customer locations in orange.

How much am I paid? You are paid based on your profit.

Each unit of ice cream that you sell costs you 50. The other seller also has a cost of 50 per unit.

Your profit for the day is the sum of three parts:

Morning Profit = (Morning Price – Cost of 50) × Number of Morning Customers

Repeat Customer Profit = (Repeat Customer Price – Cost of 50) × Number of Repeat Customers

New Customer Profit = (New Customer Price – Cost of 50) × Number of New Customers

[CASES 1 & 3]

There is one customer per yard. So the number of morning customers that you serve is equal to the morning cutoff point. Your repeat customers in the afternoon include everyone who bought from you in the morning and is now closer to you than the cutoff for your repeat customers in the afternoon. Thus your number of repeat customers is calculated as the repeat customer cutoff × the fraction of the buyers who visit you in the morning. This fraction equals the morning cutoff ÷ 120. Your new customers in the afternoon include everyone who did not buy from you in the morning and is now closer to you than the cutoff for your new customers in the afternoon. Thus your number of new customers is calculated as the new customer cutoff × the fraction of the buyers who did not visit you in the morning. This fraction equals the (120 – morning cutoff) ÷ 120.

[CASES 2 & 4]

There is one customer per yard. So the number of morning customers that you serve is equal to the morning cutoff point. Your repeat customers in the afternoon include everyone who bought from you in the morning and is closer to you than the cutoff for your repeat customers in the afternoon. Thus your number of repeat customers is calculated as the repeat customer cutoff. Your new customers in the afternoon include everyone who did not buy from you in the morning and is closer to you than the cutoff for your new customers in the afternoon. Thus your number of new customers is calculated as the new customer cutoff – morning cutoff.

[End CASES]

The experiment lasts for several days, but neither you nor anyone else in the experiment knows how many. After each day, the table on your screen will be updated so you have a record of the day's prices, the number of morning, new and repeat customers you served, and your profit. Your profit for the experiment is your cumulative earnings from each day. All the monetary amounts in the experiment are in lab dollars. At the end of the experiment your lab dollar earnings will be converted to $US at the rate 2500 Lab Dollars = $0.10 and this is the amount that you will be paid in cash (in addition to the $5 you are receiving for participating).

Each day the customers are new, so they do not know what prices were charged on previous days nor do they care what prices will be charged on future days.

The person in the experiment making decisions for the other ice cream shop in your market is randomly determined at the beginning of each and every day. Further, no one will ever know the identity of the other seller in the market at any point.

When you are done reading the instructions, raise your hand.

Appendix B. Review Questions

The following questions are designed to ensure that everyone understands the experiment before we begin. Your answers will not impact your payoff in any way and you should feel free to ask questions at any point. Once you are done answering the questions, please raise your hand so that an experimenter can verify your answers.

Question 1. Suppose that in the morning, you served customers up to the cutoff 80 yards away from you (so the other 40 customers went to the other seller). If your price for repeat customers is 170 and the other seller's price for new customers is 110, how many repeat customers will you have that afternoon? __________

Question 2. Suppose that you set the following prices:
Your Morning Price = 150
Your Afternoon Price for Repeat Customers = 150
Your Afternoon Price for New Customers = 100
If you have 60 customers in the morning, 30 repeat customers in the afternoon, and 40 new customers in the afternoon, then your profit would be ________

Question 3. You have to charge the same price to repeat and new customers.
True or False

Question 4. In the morning, you will set your price for (afternoon) repeat customers.
True or False

Question 5. In the morning, you will set your price for (afternoon) new customers.
True or False

Question 6. If a customer was close to you in the morning then in the afternoon that customer

a. will be close to you as customers are in the same place in the morning and afternoon.
b. could be anywhere as customer's locations are randomly picked in the afternoon.