Sequential Pricing: Theory and Experiments*

October 2008

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Advances in technology enable sellers to price discriminate based upon a customer's previous purchase decision. E-tailers can track items already in a shopping cart and item level RFID tags enable retailers to do the same in bricks and mortar stores. As retailers attempt to leverage the information made available from these technologies, it is important to understand how this new visibility impacts pricing and market outcomes. This paper examines the theoretical implications of sequential pricing in monopoly markets under three relationships among the goods or services under consideration. Specifically, the paper focuses on goods that have independent values, goods that have values which are positively or negatively correlated, and goods with super-additive or sub-additive values (i.e. complements or substitutes). The results indicate that sequential pricing increases profit relative to simultaneous pricing when the goods are substitutes. Further, when sellers can condition the second good's price on the buyer's decision to purchase the first good, sequential pricing increases profits relative to mixed bundling when the goods are highly positively correlated. The paper also uses experiments to examine sequential pricing in competitive markets where a portion of the customers comparison shop. The behavioral results indicate that conditional pricing does not lower social welfare or harm consumers when customers observe prices sequentially. Further, the ability to price discriminate does not change the price of the initially offered good, but does change the price of the second good. A comparison with previous bundling experiments suggests that sellers may be better able to extract surplus from consumers using sequential pricing rather than bundling.

Key Words: Sequential Pricing, Price Discrimination, E-commerce, Market Experiments

* The authors with to thank the Center for Retailing Excellence and the Information Technology Research Institute, both of the Sam M. Walton College of Business, for support.

1. Introduction

Imagine walking into a large department store and searching for a new outfit. The buyer observes a variety of shirts with posted prices, selects one, and then moves on to an area containing pants. The price of each pair of pants was set before the buyer selected a shirt and therefore the seller was dealing with a simultaneous price setting problem. Now imagine that the seller is able to identify which shirt the customer selected before setting the prices of the pants. The shirt selection reveals information about the buyer's tastes and preferences, thereby enabling the seller to better estimate the buyer's willingness to purchase each specific pair of pants. The seller could then effectively raise the price for items that are more likely to be purchased, perhaps by offering a smaller coupon for coordinating pants than for other pairs. Recent advances in technology have enabled exactly this type of monitoring of buyer purchases, so that pricing decisions for multiple products can be sequential rather than simultaneous.

In many market situations, buyers plan to purchase multiple SKUs (Stock-Keeping Units) and often end up purchasing additional impulse items such as those displayed at the checkout stand. Sellers seeking to increase sales revenues, as well as to target specific customer segments, have traditionally been forced to rely upon ex-ante pricing promotions. The literature documents this simultaneous pricing problem in detail. Rather than just relying upon selling individual items (pure components), traditional sellers have exploited information on the underlying distribution of preferences among goods by selling a collection of items in a bundle. Pure bundling refers to offering only the bundle, whereas mixed bundling refers to offering both the individual items and the bundle simultaneously. Due to technology enabled monitoring, now sellers can condition the price of some products on the buyer's revealed decision to purchase (or not purchase) other products. The current research investigates how information on buyers' valuations, revealed by their initial intent to purchase one item, can be leveraged by the seller to make optimal pricing decisions for subsequent potential purchases.

Consider the situation where two people X and Y each value two products A and B. Specifically, $V_A^X = V_B^X = 100$ and $V_A^Y = V_B^Y = 20$ and the value of the consuming the bundle containing both products is $V_A^i + V_B^i$ for $i = X,Y$. For simplicity, assume that the marginal cost of each product is 0. Under pure components, the maximum attainable profit is \$200, reaped by selling both products at a price of \$100 to X. Under pure bundling, the maximum profit is again \$200 and generated by selling the bundle at a price of \$200 to person X. With mixed bundling, the firm can again earn a maximum of \$200, all from person X, who will purchase both goods. Notice that if the single item price is \$20, then Y would buy both items separately (assuming the person can create his or her own bundle), but person X would buy both items as well resulting in a profit of only \$80. However, under sequential pricing with discrimination, the seller can obtain a maximum profit of \$220. Assuming that the decision to purchase A is made first, the seller can set a price of good A of \$100. Person X will purchase A and person B will not. The seller can then set a good B price of \$100 for those who purchased A and a price of \$20 for those who did not. In this case both people would buy good B. Without the ability to price discriminate, the seller could only obtain \$200, all from person X, even with sequentially set prices.

The preceding illustration motivates the current research – what is the optimal pricing strategy for sellers who can monitor a customer's initial purchase decision? The problem of conditional sequential pricing is one of first being able to identify the customer's action and then exploiting this knowledge. This first aspect is straightforward in online markets where buyers place items in electronic shopping carts. However, a relatively small proportion (3.4% in the fourth quarter of 2007) of total retail sales are online. The online component, however, is growing, as online sales in 2006 were only 2.9% of total retail sales (US Census Bureau, 2008). Currently, RFID (radio frequency identification)technology is being used to monitor which products buyers in bricks and mortar stores have in their physical shopping carts. Such technology is being employed primarily for theft detection, but other applications are being explored by industry and academia (Cromhout et al. 2008). Retailers, such as the Dillard's department store among others, have introduced item level tagging in pilot stores and are planning expansion of the program. Sam's Club, Walmart's retail warehouse club division, is expanding on its previous pallet level tagging mandate, recently introduced an item level tagging mandate for its suppliers, requiring that they tag all items shipped to 22 distribution centers by 2010 (Weier 2008). The chain is poised to unveil a new checkout format that will enable RFID enabled customer checkouts that will considerably facilitate the process and inventory control.

In terms of optimizing pricing, it does a seller no good to know that someone has purchased or intends to purchase an item if the seller does not know how the buyer's value for the item is related to the buyer's value for another item. However, sellers now have access to vast databases that can be mined to determine underlying relationships in buyer values across goods. Technology enables retailers to identify the contents of every shopping basket sold. If purchases are made with credit or debit cards or some other form of identification such as a frequent buyer cards, a customer's shopping history within and across retailers can be compiled. Techniques like collaborative filtering, which is based on others' preferences, and content filtering, which is based on preferences for product attributes, enable websites such as Amazon.com to provide recommendations to specific customers for other products. Ansari et al. (2000) point out that among other sources, a customer's preferences or choices is information that can be used to make recommendations to customers.

This research considers two ways in which a buyer's value for two products might be related – the gain or loss from consuming the goods together and the degree of correlation between the valuations of the two goods. Two products which have greater utility to a customer when they are consumed together are complements; the values of the two items are superadditive in that the bundle is worth more than the sum of its parts. Similarly two products are substitutes if the value of consuming both is less than the sum of values from consuming the single items; that is the values are subadditive. Notice that the complements/substitutes relationship is distinct from the correlation between the values of the two goods. Two books on a related topic can be substitutes or complements depending on their content, but people who dislike the topic will likely have a low value for both, while people who like the topic will likely have a high value for both.

Conditional sequential pricing may be classified as a form of third degree price discrimination (Pigou 2006). Ayres (2007) gives many examples of firms that currently engage in such practices, ranging from the most visible examples of supermarkets to those less visible such as Harrah's casinos.

Harrah's records real-time data on players winning or losing, and in combination with demographic information, uses this information to offer complementary promotional benefits to players who lose more than a critical threshold amount. In this way they avert these players leaving with a negative experience from their visit to the casino.

To our knowledge, the literature is silent on how using the same information that enables sellers to make recommendations could be used to set sequential prices. However, once item level RFID or some similar technology emerges into the mainstream, retailers will likely seek opportunities to further utilize the technology to gain benefits other than the efficient management of inventories. Among these possibilities is the opportunity to leverage the same insight into planned purchases that will be available in stores as is already available online. When this happens in the near future, the benefits from optimal deployment of sequential pricing practices will have potential impact on a scale far beyond that imaginable even a few years ago. The theoretical results presented in this paper suggest that sequential pricing with discrimination outperforms mixed bundling when the goods have highly positively correlated values. Sequential pricing even without discrimination is more profitable then simultaneous pricing of pure components when the goods are close substitutes.

It is important to note that the ability to set sequential discriminatory prices does not only help the seller, but is also potentially beneficial to buyers. In the numerical example above, under sequential pricing with discrimination, person *Y* is able to purchase good *B,* which would not be the case otherwise. It is also easy to imagine situations where the *B* product is one with which the buyer was unfamiliar initially. The desire to generate profits will lead sellers to make buyers aware of more potentially valuable products. Ayres (2007) lists many naturally occurring examples of collaborative filtering generating recommended products that the buyer would not have been aware of otherwise, thus increasing a buyer's overall satisfaction.

The rest of this paper is organized as follows: Section 2 reviews research on pricing relevant to the current research framework. Section 3 outlines an analytical framework that models sequential pricing decisions faced by a monopolist. Section 4 considers the problem faced by firms which compete for buyers of the initial good. The theoretical model is described and experiments are presented to demonstrate how human decision makers perform when making sequential pricing decisions and the likely market outcomes. In Section 5 we summarize the results.

2. Literature Review

Research on sequential pricing and exploiting the underlying relationship among the goods is surprisingly sparse given the rapid ongoing proliferation of technologies that enable retailers to gather information on planned purchases that may be used to optimize profits by means of pricing of candidate goods for subsequent purchases. Mulhern and Leone (1991) review multi-product pricing and develop a framework for retail pricing and promotion policies. Using empirical data, they estimate the influence of regular and promotional prices on sales of substitute and complementary goods, and thus demonstrate the effectiveness of price promotions as a means of exploiting interdependencies in demand among retail products.

Instead, the literature on selling multiple products has been primarily focused on bundling by monopolists.[1] Bundling has been shown to be an effective price discrimination tool even when the consumer's willingness to pay for each good is independent of the value of the other good and the value of the bundle is the sum of the values of the components (Adams and Yellen 1976). Customers with a high degree of asymmetry in product valuations will buy an individual product that they favor, while customers with more symmetric valuations will buy the bundle.[2] Venkatesh and Kamakura (2003) present an analytical model of contingent valuations and find that the degree of complementarity or substitutability in conjunction with marginal cost levels determines whether products should be sold as pure components, pure bundles, or mixed bundles. They also find that typically, complements and substitutes should be priced higher than independently valued products. Nettesine, Savin, and Xiao (2006) present a stochastic dynamic program for analyzing the selection of complementary products.

There are some studies of dynamic pricing of goods, although these are confined to single goods and do not consider cross category effects on other goods. Cope (2006) presents dynamic strategies for maximizing revenue in internet retail by actively learning customers' demand responses to price. Zhang and Krishnamurthi (2004) provide a decision support system of micro-level promotions in an internet shopping environment, that provides recommendations as to when, how much, and to whom to give price promotions. The system derives the optimal price promotion for each household, on each shopping trip by taking into account the time-varying pattern of purchase behavior and the impact of the promotion on future purchases.

There are several examples of sellers using customer behavior to infer preferences, and using that information either to drive revenues or for customer relationship management. Moon and Russell (2008) develop a product recommendation model based on the principle that customer preference similarity stemming from prior purchase behavior is a key element in predicting current purchase. Montgomery et al. (2004) show how clickstream data about the sequence of pages or path navigated by web buyers can be used to infer users' goals and future path. The current research studies how buyer preferences that may be inferred from initial purchase decisions, in conjunction with distributions of values estimated from historic data, can be used to set optimal prices for subsequent purchases.

3. Sequential Pricing in Monopoly Conditions

3.1 *Monopolist's Problem*

[1] There are a few studies of price bundling in competitive markets. McAfee, McMillan, and Whinston (1989) extend their monopoly results to a duopoly and show that independent pricing can never be a Nash equilibrium when the reservation prices for the single goods are independent. Chen (1997) analyzes a situation in which firms compete in a duopoly for a single product and the firms also produce other products under conditions of perfect competition. Bundling as a product differentiation device proves to be an equilibrium strategy for one or both of the firms. Aloysius and Deck (2008) report behavioral experiments in a theoretically intractable general framework where firms engage in bundling while competing for informed customers and maintaining monopoly power over uninformed customers. Their results indicate that sellers tend to be overly competitive, using bundling as a competitive weapon rather than as a tool for price discrimination.

[2] Schmalensee (1984) finds similar results in a model with continuous (bivariate normal) valuations. McAfee, McMillan and Whinston (1989) provide conditions under which such bundle pricing is optimal. Hanson and Martin (1990) show how to compute optimal bundle prices using a mixed integer linear program.

We begin with the simple assumption of a monopolist facing a pricing decision in two sequentially ordered markets. The products may be substitutes, complements, or neither. However, it is assumed that the consumer's value for one item is distributed independently of the other. In other words, the value of the product purchased second may depend on whether the initial good was purchased, but the values of the two goods separately are not correlated. Of course, the optimal pricing strategy depends upon whether the monopolist can use information regarding the consumer's decision in the market for the first good when setting the price for the second good. We first consider the case in which the monopolist cannot use such information and then follow that with an analysis of the case in which the monopolist is able to price discriminate in the market for the second good.

Before considering these two cases in turn, it is useful to note that sequential pricing in the absence of price discrimination is substantively different from simultaneous pricing. The sequential pricing problem is one in which the monopolist recognizes the impact of the price of good A on the purchase of good B. By recognizing the behavioral response at the second stage (good B decision) to the outcome in the first stage (good A decision), the monopolist will consider those results in expectation when pricing good A. Consumer behavior differs in that the sequential problem does not provide the consumer with full information when making a choice. Rather, the consumer in this model will choose to purchase A solely on its price relative to value and then a choice regarding B will occur subsequently. Given that consumer behavior is entirely different due to the timing effects, the pricing strategy also is entirely different. As such, it is important to fully model the case of sequential pricing absent price discrimination.

We begin with the general market set-up and then consider the each case in turn. Assume a market exists for two products denoted *A* and *B*, and a consumer has a choice first to buy A followed by a choice to buy B in sequence. Let the consumer's value for *A* be distributed $V_A \sim \mathrm{f}_A(V_A)$. Then the consumer will buy *A* iff $P_A \leq V_A$. Similarly, the consumer's independent value for B follows the distribution $V_B \sim \mathrm{f}_B(V_B)$. Following Venkatesh and Kamakura (2003), a consumer's joint value from *A* and *B* is denoted $V_{AB} = (1+\theta)(V_A + V_B)$, where θ represents complementarity if $\theta > 0$, and substitutability if $\theta < 0$. A consumer who chooses not to purchase *A* will buy *B* iff $P_B \leq V_B$. However, if *A* was purchased, then the joint value becomes relevant and the consumer will buy *B* iff $P_B < (1+\theta)(V_A + V_B) - V_A$ which can be rewritten as $V_B > \frac{P_B - \theta V_A}{1+\theta}$. A consumer will purchase only one unit of either item, and the monopolist produces each item at constant marginal costs of C_A and C_B respectively.

Given this framework, now consider a monopolist's problem in setting prices.

<u>Case 1</u>: <u>Monopoly Pricing without Price Discrimination</u>

When the monopolist sets P_B, it is as if there is no information concerning the decision to buy *A*. Rather, the monopolist will know the probability that *A* will have been chosen, conditional on the price of *A* and the distribution of preferences. Similarly, the monopolist sets the price of *A* knowing the probability *A* will be bought and therefore, how that probability will affect the subsequent purchase of *B*. Let us consider these stages in reverse. In other words, conditional on a price of *A* and the corresponding probability that *A* was purchased, how then should the monopolist price *B*? And then, given that follow-up to a price of *A*, how should the monopolist price *A* in the first place?

Stage 2: Price of B

The monopolist will maximize expected profit with respect to the price of *B* conditional on a price of *A* and the distributions over preferences. If a sale is made, profits are simply P_B-C_B and if not, profit is zero. The monopolist maximizes equation (1).

$$\max_{P_B} E\Pi(\mathrm{P_B}|\mathrm{P_A}) = (P_B - C_B)\int_{P_B}^{\infty}\int_0^{P_A} f_A(V_A)f_B(V_B)dV_A dV_B + (P_B - C_B)\int_{P_A}^{\infty}\int_{\frac{P_B-\theta V_A}{1+\theta}}^{\infty} f_A(V_A)f_B(V_B)dV_B dV_A \quad (1)$$

The first term is profit from those who buy *B* but not *A* and the second term is profit from those who buy both *B* and *A*. Differentiating (1) with respect to P_B and solving for P_B*= f(P_A) gives an optimal response function based upon the choice in the first market.

Stage 1: Price of A

Given P_B*, the monopolist must choose the optimal P_A for stage 1 by maximizing expected profit for the sum of both stages, recognizing that the choice of P_B depends on P_A. In stage 1, the monopolist maximizes equation (2).

$$\max_{P_A} E\Pi(P_A = (P_A - C_A)\int_{P_A}^{\infty}\int_0^{\frac{P_B^*-\theta V_A}{1+\theta}} f_A(V_A)f_B(V_B)dV_A dV_B + (P_B^* - C_B)\int_{P_B^*}^{\infty}\int_0^{P_A} f_A(V_A)f_B(V_B)dV_A dV_B + (P_A - C_A + P_B^* - C_B)\int_{P_A}^{\infty}\int_{\frac{P_B^*-\theta V_A}{1+\theta}}^{\infty} f_A(V_A)f_B(V_B)dV_A dV_B \quad (2)$$

where the first term is profit from those who buy *A* only, the second term is profit from those who buy *B* only, and the third term is the profit from those who buy both. The general solution is derived by finding the first order condition of (2) with respect to P_A, solving this first order condition for P_A* and then calculating P_B*.

This exercise is intractable in general, so we now consider the case of a uniform distribution for consumer preferences. Specifically, let $f_A(V_A) \sim U[0,100]$ and $f_B(V_B) \sim U[0,100]$. In this case (1) can be rewritten as

$$\max_{P_B} E\Pi(\mathrm{P_B}|\mathrm{P_A}) = (P_B - C_B)\int_{P_B}^{100}\int_0^{P_A}\frac{1}{100^2}dV_A dV_B + (P_B - C_B)\int_{P_A}^{100}\int_{\frac{P_B-\theta V_A}{1+\theta}}^{100}\frac{1}{100^2}dV \quad (1')$$

After integrating and simplifying (1′) the problem becomes

$$\max_{P_B} E\Pi(\mathrm{P_B}|\mathrm{P_A}) \;= \frac{(P_B - C_B)}{100^2}[100^2 - P_A P_B + \frac{P_B}{1+\theta}(P_A - 100) + \frac{\theta}{1+\theta}\left(\frac{100^2 - P_A^2}{2}\right)] \qquad (1'')$$

Differentiating (1′′) with respect to P_B and simplifying the first order condition yields

$$P_B^* = \frac{C_B(P_A\theta - 100) - \frac{100^2}{2}(2+3\theta) + \frac{\theta P_A^2}{2}}{-2(P_A\theta + 100)} \qquad (3)$$

Performing the same exercise for equation (2) using uniform distribution, (2) can be rewritten as

$$\max_{P_A} E\Pi(\mathrm{P_A}) = (P_A - C_A)\int_{P_A}^{100}\int_0^{\frac{P_B^* - \theta V_A}{1+\theta}} \frac{1}{100^2}\, dV_A dV_B \;\; +$$

$$(P_B^* - C_B)\int_{P_B^*}^{100}\int_0^{P_A} \frac{1}{100^2}\, dV_A dV_B + (P_A - C_A + P_B^* - C_B)\int_{P_A}^{100}\int_{\frac{P_B^* - \theta V_A}{1+\theta}}^{100} \frac{1}{100^2}\, dV_A dV_B \qquad (2')$$

Integrating (2′) and simplifying yields (2′′)

$$\max_{P_A} E\Pi(\mathrm{P_A}) \;= \frac{(P_A - C_A)}{100^2}\left[100^2 - P_A P_B^* + \frac{P_A P_B^* - 100 P_B^*}{1+\theta} + \frac{\theta}{2(1+\theta)}(100^2 - P_A^2)\right] \qquad (2'')$$

where P_B^* is found in equation (3). Solving the first order condition for (2′′) we need to differentiate with respect to P_A given that P_B is a function of P_A and P_B can be found from (3). The solution is quite cumbersome, but can be found using Mathematica. We do note that when $C_A = C_B = \theta = 0$ we can find $P_A^* = 50$, $P_B^* = 50$ which is precisely the optimal monopoly price in the two independent markets taken separately.

<u>Case 2: Monopoly Pricing with Price Discrimination</u>

In this case the monopolist will know when setting the price of B whether the consumer has purchased A or not. Formally, the decision is to choose either $P_B|q_A=0$ or $P_B|q_A=1$ where $q_A=0$ if A was not purchased and $q_A=1$ otherwise. In other words, the monopolist selects a state contingent price for good B.

Stage 2: Price of B if $q_A=0$, i.e. $V_A < P_A$

Since the buyer's values for A and B are independent and since A is not purchased, the monopolist's problem is to maximize

$$E\prod(P_B|q_A = 0) = (P_B - C_B)\int_{P_B}^{\infty} f_B(V\,)dV_A \qquad (4)$$

Taking the first order condition of (4) and solving yields $P_B^*|q_A=0$.

For the uniform distribution example (4) simplifies to (4′).

$$(P_B - C_B)\int_{P_B}^{100} \frac{1}{100}\, dV_B = \left(\frac{P_B - C_B}{100}\right)(100 - P_B) \qquad (4')$$

Maximizing (4 ′) with respect to P_B and solving yields $P_B^*|(q_A = 1) = \frac{100+C_B}{2}$. When θ=0 and C_B=0 we get the standard monopoly solution of P_B^*=50.

Stage 2: Price of B if q_A=1, i.e. $V_A \geq P_A$

In this case the monopolist considers the joint valuation of both products when pricing B. In other words, $V_{AB} = (1+\theta)(V_B + V_A)$. Thus, the marginal value of B $= (1+\theta)(V_B + V_A) - V_A$ and the consumer will buy B iff $P_B \leq (1+\theta)(V_B + V_A) - V_A = (1+\theta)(V_B) - \theta V_A$. Therefore, the consumer will buy B iff $\frac{P_B - \theta V_A}{1+\theta} \leq V_B$.

Given this information, the monopolist chooses to maximize equation (5).

$$\max_{P_B} E\prod(P_B|q_A = 1) = \left((P_B - C_B) \int_{PA}^{\infty} \int_{\frac{P_B - \theta V_A}{1+\theta}}^{\infty} f(V\,B) f(VA|VA > PA)\, dV_B dVA \right) \qquad (5)$$

Taking the first order condition of (5) and solving yields P_B^* | q_A=1.

Under the assumption of the uniform distribution this can be rewritten as (5 ′).

$$\max_{P_B} E\prod(P_B|q_A = 1) = \left((P_B - C_B) \int_{PA}^{100} \int_{\frac{P_B - \theta V_A}{1+\theta}}^{100} \frac{1}{100} \frac{1}{100 - PA} dV_B dVA \right)$$

$$= \frac{P_B - C_B}{100} \left(100 - \frac{P_B - \theta(100 - P_A)/2}{1+\theta} \right) \qquad (5\,')$$

Taking the first order condition of (5 ′) and solving for the price of B yields

P_B^* = $\frac{100(1+\theta) + \theta(100 - P_A)/2 + C_B}{2}$. Note that once again when θ=0 and C_B=0 we get the standard monopoly solution of P_B^*=50.

Stage 1: The Price of A

We now need to solve for P_A given what will occur in stage 2. Specifically we need to know $E\prod$ when q_A=0 or q_A=1. Plugging the solution for P_B^* | q_A=0 and P_B^* | q_A=1 into (4) and (5) respectively gives the expected profit in each state. The monopolist will maximize total expected profit over both stages, knowing both the probability that A will be purchased at a given price and the resulting expected profits in stage 2 based on the follow-up price of B. The objective function then can be written as

$$E\prod(P_A) = Prob(q_A = 0) * E\prod_B(q_A = 0) + Prob(q_A = 1)(\,(E\prod_A(q_A = 1) + E\prod_B(q_A = 1)) \qquad (6)$$

In general this problem is not tractable, but again we can set it up for the uniform case and find the solution. Recall that when q_A=0, P_B = $\frac{100+C_B}{2}$. Computing the resulting profit yields

$E\prod = (\mathrm{P_B} - \mathrm{C_B}) \int_{\frac{100-C_B}{2}}^{100} \frac{1}{100} \mathrm{dV_B}$ which can be simplified to $E\prod_B(q_A = 0) = 25 - \frac{C_B}{2} + \frac{C_B^2}{4(100)}$.

When q_A=1, $P_B = \frac{100(1+\theta)+\theta(100-P_A)/2+\mathrm{C_B}}{2}$ which yields a corresponding expected profit of

$E\prod_B(q_A = 1) = (\mathrm{P_B} - \mathrm{C_B}) \int_{\mathrm{PA}}^{100} \int_{\frac{P_B-\theta V_A}{1+\theta}}^{100} \frac{1}{100} \frac{1}{100-\mathrm{PA}} \mathrm{dV_B dV_A}$ which simplifies to

$E\prod_B(q_A = 1) = \frac{1}{200}(100(1+\theta) + \theta(100 - P_A)/2 \quad - \mathrm{C_B})\left(50 + \frac{\theta(100-P_A)/2-C_B}{(1+\theta)}\right)$

Therefore, for the uniform case we have that (6) can be rewritten as follows.

$$\begin{aligned} E\prod(P_A) = {} & \left(\int_0^{\mathrm{P_A}} \frac{1}{100} \mathrm{dV_A}\right)\left(25 - \frac{C_B}{2} - \frac{C_B^2}{400}\right) \\ & + \left(\int_{\mathrm{P_A}}^{100} \frac{1}{100} \mathrm{dV_A}\right)\Bigg(\mathrm{P_A} - \mathrm{C_A} \\ & + \frac{1}{200}(100(1+\theta) + \theta(100 - P_A)/2 \quad - \mathrm{C_B})\left(50 + \frac{\theta(100 - P_A)/2 \quad - C_B}{2(1+\theta)}\right)\Bigg) \end{aligned}$$

$$= \frac{1}{100}\left(\mathrm{P_A}\left(25 - \frac{C_B}{2} - \frac{C_B^2}{400}\right) + \frac{(100 - \mathrm{P_A})}{100}\left(\mathrm{P_A} - \mathrm{C_A} + \frac{1}{200}(\ldots)(\ldots)\right)\right)$$

The first order condition is that

$25 - \frac{C_B}{2} - \frac{C_B^2}{400} + 100 - 2\mathrm{P_A} + \mathrm{C_A} -$
$\frac{1}{200}(100(1+\theta) + \theta(100 - P_A)/2 \quad - \mathrm{C_B})\left(50 + \frac{\theta(100-P_A)/2 \quad -C_B}{2(1+\theta)}\right) = 0.$

Solving for $\mathrm{P_A}$ yields $P_A^* = \frac{50 - C_B + \frac{C_B^2}{200} + 100 + C_A - \frac{1}{100}(100(1+\theta)+\theta(100-P_A)/2 \quad -\mathrm{C_B})\left(50 + \frac{\theta(100-P_A)/2 \quad -C_B}{2(1+\theta)}\right)}{2}$.

As above, when θ=0, C_B=0 and C_A=0 we find the standard monopoly price P_A^*=50.

3.2 Impact of the ability to conditionally price

In the special case where θ=0 and the values are independently distributed, the purchase of good A has no direct effect on the buyer's value for good B (the goods are neither complements or substitutes when θ=0) and knowing that $V_A \geq P_A$ provides no information to the seller as to the likely values of V_B. Therefore, P_B should be the same for everyone even if the seller could set conditional prices and this will be the same price that would be charged if the seller could not discriminate. With C_A=0 and C_B=0, the price is 50 for all three buyer types.

In general these three prices and the resulting profits will differ if the goods are complements or substitutes. Given the complexity in the solutions above, in Table 1 we provide a numerical comparison of sequential pricing with and without the ability to price discriminate for goods with independent

Table 1. Numerical Comparison of Sequential Pricing with and without Discrimination

θ	ρ	Sequential Pricing without Discrimination			Sequential Pricing with Discrimination				Distribution of Values
		P_A	P_B	$E(\Pi)$	P_A	$P_B \mid q_A=1$	$P_B \mid q_A=0$	$E(\Pi)$	
-0.5	0	63	50	39.45	62	7	50	39.66	V_A~U[0,100] V_B~U[0,100]
-0.4	0	63	50	39.45	61	14	50	40.69	
-0.3	0	58	37	40.32	58	23	50	42.47	
-0.2	0	56	41	43.81	56	32	50	44.72	
-0.1	0	53	46	47.17	53	42	50	47.39	
0	0	50	50	50.50	50	50	50	50.50	
0.1	0	48	55	53.46	48	59	50	53.63	
0.2	0	46	59	56.45	46	68	50	57.11	
0.3	0	43	63	59.32	44	76	50	60.72	
0.4	0	40	68	62.23	41	84	50	64.60	
0.5	0	37	73	65.13	39	93	50	68.64	
0.6	0	35	78	67.89	38	101	50	72.62	
0.7	0	32	83	70.80	36	110	50	76.86	
0.8	0	24	116	74.05	34	117	50	81.27	
0.9	0	22	124	78.83	33	126	50	85.67	
1	0	21	131	83.93	31	133	50	90.38	
0	-1.0	50	50	50.50	43	29	58	57.71	$V_A, V_B \in[0,100] \mid V_A + V_B = 100$
0	-0.85	47	47	50.73	46	27	58	54.72	$V_A, V_B \in[0,100] \mid 75 \leq V_A + V_B \leq 125$
0	-0.75	46	46	50.91	47	30	56	53.63	$V_A, V_B \in[0,100] \mid 67 \leq V_A + V_B \leq 133$
0	-0.5	45	45	51.36	46	39	50	51.89	$V_A, V_B \in[0,100] \mid 50 \leq V_A + V_B \leq 150$
0	-0.25	48	48	50.67	48	45	50	50.75	$V_A, V_B \in[0,100] \mid 33 \leq V_A + V_B \leq 167$
0	-0.15	49	49	50.55	49	47	50	50.58	$V_A, V_B \in[0,100] \mid 25 \leq V_A + V_B \leq 175$
0	0	50	50	50.50	50	50	50	50.50	$V_A, V_B \in[0,100]$
0	0.15	49	49	50.55	49	50	47	50.58	$V_A, V_B \in[0,100] \mid \lvert V_A - V_B\rvert \leq 75$
0	0.25	48	48	50.67	48	50	45	50.76	$V_A, V_B \in[0,100] \mid \lvert V_A - V_B\rvert \leq 67$
0	0.5	45	45	51.36	45	50	36	52.08	$V_A, V_B \in[0,100] \mid \lvert V_A - V_B\rvert \leq 50$
0	0.75	46	46	50.91	47	54	28	53.61	$V_A, V_B \in[0,100] \mid \lvert V_A - V_B\rvert \leq 33$
0	0.85	47	47	50.73	49	56	25	54.52	$V_A, V_B \in[0,100] \mid \lvert V_A - V_B\rvert \leq 25$
0	1	50	50	50.50	58	58	29	57.71	$V_A, V_B \in[0,100] \mid \lvert V_A - V_B\rvert = 0$

V_A, $V_B \in$ [0,100]|ξ indicates that the pair (V_A, V_B) is drawn uniformly from the subset of [0,100]×[0,100] that satisfies condition ξ.

values where the additivity in bundle values varies from θ=-0.5 to θ=1.0. The above analysis does not examine the situation where the underlying values for the two goods are not independent. While there are many distributions that one could use for such analysis, the choice is arbitrary unless one has information about a specific set of naturally occurring product markets, which are unlikely to follow a normal, uniform, or any other mathematically nice distribution. Therefore, we offer a numerical comparison for a series of distributions where the correlation varies from ρ=-1 to ρ=1. Specifically, the distributions used for this comparison are created by removing the opposing corners from the square domain [0,100] × [0,100]. These distributions are easy to describe in a manner similar to the independent values case, thus making them appropriate for behavioral exploration in the laboratory.

As one would expect, the ability to price discriminate increases profitability for the monopolist. Further, if the seller were forced to charge a single price for good B, this price would lie somewhere between the two prices that would be charged if discrimination were possible, a result similar to standard third degree price discrimination. The profit increase becomes more pronounced as θ or ρ become more distant from 0. When the goods are not correlated, those who did not purchase good A observe the same price for good B that the monopolist would have charged if the markets had been treated separately. For those who did buy good A, the price for B will be lower (higher) with sequential pricing then it would have been if the monopolist treated the goods separately when the goods are substitutes (complements). Finally, we note that sequential pricing without price discrimination is symmetric with respect to correlation. That is, the set of prices and the resulting profits are based upon $|\rho|$.

3.3 *Comparison of sequential pricing with simultaneous pricing*

Venkatesh and Kamakura (2003) explore the optimal bundle prices for a similar framework again under the assumption of a uniform distribution with independently distributed values. The complexity of both models makes a direct theoretical comparison difficult. However, it is a reasonable to ask if sequential price discrimination outperforms traditional mixed bundling. To explore this, we again offer a numerical comparison (see Table 2). For completeness, we also include the optimal prices and profits for a monopolist that charges a single simultaneous price for each good (i.e. pure components).

The results indicate that sequential pricing with discrimination can outperform mixed bundling when the goods are very close substitutes (θ=-0.4,-0.5). This result is somewhat intuitive in that when the goods are close substitutes, mixed bundling essentially gives the second product away. Sequential pricing allows the seller to exploit more fully those buyers who have a high value for both goods by charging them a (still very small) but larger marginal price for the second good. Sequential pricing with discrimination can also outperform mixed bundling when the value of the goods is highly positively correlated (ρ=0.75,0.85,1.0). This is the same pattern observed in the example discussed in the introduction. The comparison of sequential pricing without discrimination and pure components, the two cases where sellers set a single price for each good, is also revealing. While the two practices lead to identical outcomes when the values of the goods are correlated, when the goods are substitutes (θ<0), sequential pricing without discrimination outperforms pure components pricing. It is also interesting to note that the benefits of mixed bundling relative to pure components seem to be greatest the closer θ is to 0 or ρ is to -1.

Table 2. Numerical Comparison of Simultaneous Pricing with Pure Components and Mixed Bundling

θ	ρ	Mixed Bundling P_A, P_B	Mixed Bundling P_{AB}	Mixed Bundling Π	Pure Components P_A, P_B	Pure Components Π	Distribution of Values
-0.5	0	58	58	38.87	58	38.87	V_A~U[0,100] V_B~U[0,100]
-0.4	0	59	61	39.96	58	38.87	
-0.3	0	61	70	42.68	58	38.87	
-0.2	0	63	75	46.26	55	39.02	
-0.1	0	64	80	50.51	49	44.06	
0	0	67	87	55.27	50	50.50	
0.1	0	80	88	60.05	52	56.40	
0.2	0	80	96	65.51	54	62.54	
0.3	0	83	109	70.85	57	68.43	
0.4	0	80	112	76.43	60	74.39	
0.5	0	82	123	81.97	63	80.50	
0.6	0	82	131	87.30	67	86.16	
0.7	0	83	141	92.82	67	92.03	
0.8	0	80	144	98.26	72	98.09	
0.9	0	80	152	103.72	76	103.66	
1	0	82	164	109.29	82	109.29	
0	-1.0	100	100	100.00	50	50.50	V_A, $V_B \in [0,100] \mid V_A + V_B = 100$
0	-0.85	75	75	75.00	47	50.73	V_A, $V_B \in [0,100] \mid 75 \leq V_A + V_B \leq 125$
0	-0.75	67	73	67.64	46	50.91	V_A, $V_B \in [0,100] \mid 67 \leq V_A + V_B \leq 133$
0	-0.5	66	79	59.87	45	51.36	V_A, $V_B \in [0,100] \mid 50 \leq V_A + V_B \leq 150$
0	-0.25	66	83	56.83	48	50.67	V_A, $V_B \in [0,100] \mid 33 \leq V_A + V_B \leq 167$
0	-0.15	67	85	56.10	49	50.55	V_A, $V_B \in [0,100] \mid 25 \leq V_A + V_B \leq 175$
0	0	67	87	55.27	50	50.50	V_A, $V_B \in [0,100]$
0	0.15	62	87	54.65	49	50.55	V_A, $V_B \in [0,100] \mid \lvert V_A - V_B \rvert \leq 75$
0	0.25	59	88	54.22	48	50.67	V_A, $V_B \in [0,100] \mid \lvert V_A - V_B \rvert \leq 67$
0	0.5	52	88	52.70	45	51.36	V_A, $V_B \in [0,100] \mid \lvert V_A - V_B \rvert \leq 50$
0	0.75	51	92	50.91	46	50.91	V_A, $V_B \in [0,100] \mid \lvert V_A - V_B \rvert \leq 33$
0	0.85	51	95	50.92	47	50.73	V_A, $V_B \in [0,100] \mid \lvert V_A - V_B \rvert \leq 25$
0	1	50	100	50.50	50	50.50	V_A, $V_B \in [0,100] \mid \lvert V_A - V_B \rvert = 0$

V_A, $V_B \in [0,100] \mid \xi$ indicates that the pair (V_A, V_B) is drawn uniformly from the subset of [0,100]×[0,100] that satisfies condition ξ.

4. Sequential Pricing in Competitive Markets with Informed and Uninformed Buyers

The above analysis focuses on the problem faced by a monopolist. However, most of the examples described in the paper occur in more competitive markets. This setting creates a tension between using prices to set up future price discrimination and attracting customers in the first place. To examine this setting, we incorporate competition á la Varian's (1980) model of sales. In this model uninformed shoppers account for a fraction α of the market and the remaining 1-α are informed.

Informed buyers observe the price of good A offered by the *n* sellers in the market. These buyers may learn of the price via online shopping comparison websites or by reading advertisements in the newspaper. If the lowest offered price is at or below the informed buyer's reservation value, then the buyer will visit the low price seller, make the purchase and then observe the price of good B and otherwise the buyer will not visit any seller and will make no purchase. In this sense, good B is a new or unknown product or an impulse type item.[3] The uninformed buyers visit only one seller, observe that seller's price of good A, make a purchase decision, and then observe the possibly conditioned price of B. These buyers can be thought of as being loyal to the seller, having a preference for a particular seller, an unawareness of competitors, or travel costs that prohibit visiting other sellers. It is assumed that an equal fraction of uninformed buyers visit each seller. Therefore each seller acts as a monopolist to α/n of the market.

Again, a seller's problem differs if the price of good B can be conditioned on the decision to purchase good A. The appropriate solution concept is a symmetric mixed strategy Nash equilibrium. First, one can note that a seller always has the option to set monopoly prices and fully exploit the fraction of uninformed customers who visit. The profit from this action is referred to as the security profit since the seller can unilaterally guarantee itself this amount. We also note that there is no pure strategy equilibrium in this game as a firm would always prefer to lower one of its prices by e and computer the entire market or receive the security profit. Since any strategy in a mixed strategy equilibrium must generate the same expected payoff, one can use then use the security payoff to implicitly define the mixing distribution. See Deck and Wilson (2006) and Aloysius and Deck (2008) for details. While the approach is intuitive, the implementation is not practical given the complexity of the problem. Therefore, we turn directly to a series of laboratory experiments for exploring the likely market outcomes of sequential pricing with and without price discrimination.[4]

4.1 Experimental Design

To explore the impact of sequential pricing in competitive markets, a total of 24 laboratory sessions were conducted. The sessions include 4 replicates of each treatment in a 3×2 design. The first dimension of the design is the relationship between two experimental goods, A and B. In the "independent values" condition, the buyer's values for the two goods are independent and the value of the bundle made from purchasing both goods is the sum of the values of the separate items (i.e. θ=0). Specifically, V_A ~ U[0,100] and V_B ~ U[0,100] in the independent values case. For the "complements"

[3] An alternative approach is to assign the informed buyer who chooses not to purchase A to some store randomly and then observe the B price there. However, it is not clear why the buyer would choose to go to the store or website if they know that they are not going to make a purchase. Another alternative is that informed sellers are aware of the price of both goods. In this case it is not clear which B price the buyer should observe if the seller is engaging in price discrimination in the B market or whether or not the buyer should be able to purchase the items from distinct sellers and if the sellers should be able to observe the buyer's shopping history at a rival's outlet.

[4] Both Deck and Wilson (2006) and Aloysius and Deck (2008) look at pricing strategies in competitive markets using controlled laboratory methods and find that observed behavior is not consistent with the limited theoretical predictions.

condition, the single item values are the same as in the previous case but the value from buying both items is $1.3(V_A + V_B)$, that is θ=0.3. The third condition involves positively "correlated values," where V_A and V_B are jointly distributed according to the density function $f(V_A,V_B)= \begin{cases} \frac{1}{7651} & if\left|V_A - V_B\right| \leq 50 \\ 0 & else \end{cases}$ for V_A, V_B integers $\in$ [0,100]. For this distribution the correlation is ρ=0.5. Bundle values are additive in the correlated values condition (i.e. θ=0). The distributions used in the laboratory are ones presented in the numerical comparisons in Tables 1 and 2.[5] The second dimension of the experimental design was the ability or inability to price discriminate by conditioning the price of good B on the buyer's decision to purchase good A.

Subjects were recruited from undergraduate courses at a state university. While many of the participants are in the business school, students from other disciplines participated as well. The students were recruited directly from classes and through the laboratory's subject database. Some of the subjects had prior experience in experiments; however, none had previously participated in any related experiments. Each laboratory session lasted 90 minutes, including approximately 30 minutes for the self paced written directions and the completion of a comprehension handout.[6] After completing the handout, responses were checked by an experimenter and any remaining questions were answered. Once all of the participants were ready, the actual experiment began.

Sessions lasted for 750 paid market periods, including 250 periods that served as practice to allow the subjects to become familiar with the interface and competitive pressures in these markets.[7] During the experiment, subjects had an onscreen tool that would identify which potential uninformed customers would buy each good and the expected profit based upon a subject specified pricing strategy. This tool is shown in Figure 1. Value combinations that would lead to purchases of good A only are shaded in yellow while value combinations that would lead to the purchase of good B only are in blue. Value combinations such that the person would buy both A and B are shaded green. Combinations for which the person would not buy anything are white and areas shaded black could not occur given the distribution of values. A subject could click on an area in the diagram on the right and the diagram on the left would focus on the specified area revealing the actual buyer values in that region. For simplicity, the marginal cost of producing both types of goods was $C_A=C_B=0$ and therefore profit and revenue are identical.

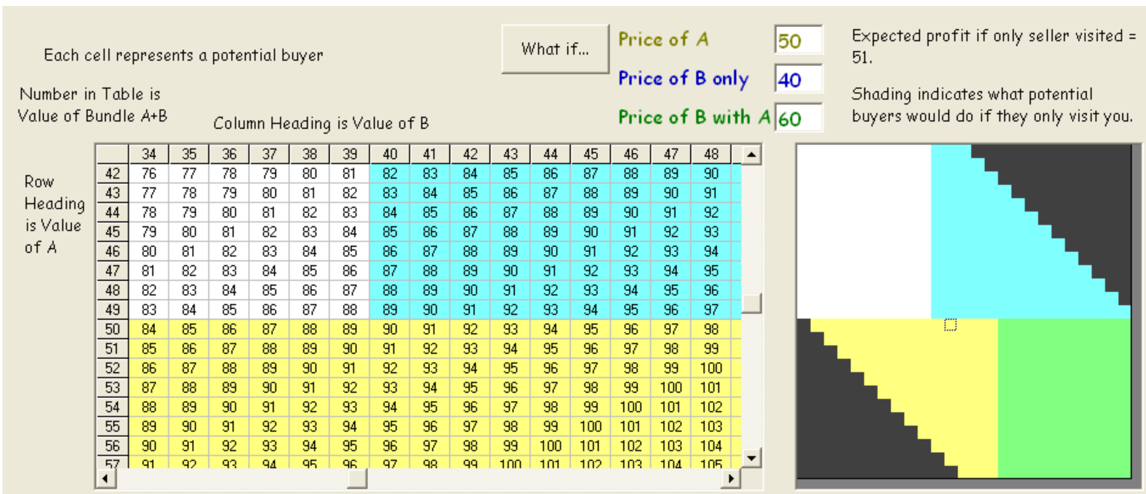
[5] The specific choices are not ones where sequential pricing are expected to outperform bundling as the main purpose of this paper is not to compare the two practices, but rather to explore the implications of sequential pricing as a novel strategy. The chosen distributions are not extreme and were selected with a eye towards the ease with which they could be explained to subjects.

[6] Copies of the directions and the handout are available from the authors upon request.

[7] Subjects did not know the total number of periods in the experiment nor were the practice periods singled out for the subjects. Subjects did know the total length of the session, but typically the experiments finished before the allotted time had expired.

Each session involved n=4 seller subjects.[8] Sellers could adjust their prices at any point and received feedback about the prices charged and profit earned by each rival after every period. In each period a single buyer would enter the market and make a purchase decision based upon their randomly determined values for goods A and B. Since buyers demand a single unit of each good, there is no incentive for them to not truthfully reveal their willingness to buy. Therefore, the buyer role was automated, a common practice in posted offer market experiments where demand withholding is not a critical element of the design (see Davis and Holt 1993).

Figure 1. Onscreen Pricing Tool – Correlated Values with Good B Price Discrimination



Loyal (or uninformed) customers accounted for a = 80% of the market so each seller served as a monopolist to α/n=20% of the market. Comparison (or informed) shoppers accounted for 1-α=20% of the market. If multiple sellers set the same price, a comparison shopper would randomly select one low price seller from whom to purchase.

At the conclusion of the experiment, subjects were paid based upon their earned profit at the rate $400 in profit = US $1. The average salient payment was approximately $18.00. Participants also received a fixed payment of $7.50 for arriving on time and participating in the study. Subjects were paid in private and were dismissed from the experiment once they had collected their money. Multiple sessions occurred concurrently in the laboratory. This prevented subjects from being able to identify which other participants were sellers in the same market. It also controlled for inadvertent noise effects that might vary from one time in the laboratory to the next.

4.2 *Experimental Results*

[8] The total number of subjects was thus 4 subjects per session × 24 sessions = 96 total subjects.

The data consist of 48,000 market pricing decisions.[9] Of course, observations from the same subject or even from the same session are not independent. Therefore, a linear mixed effects model is utilized to control for the repeated measures present in the data at the period level. Standard non-parametric tests are utilized for comparisons at the session level since each session is independent.

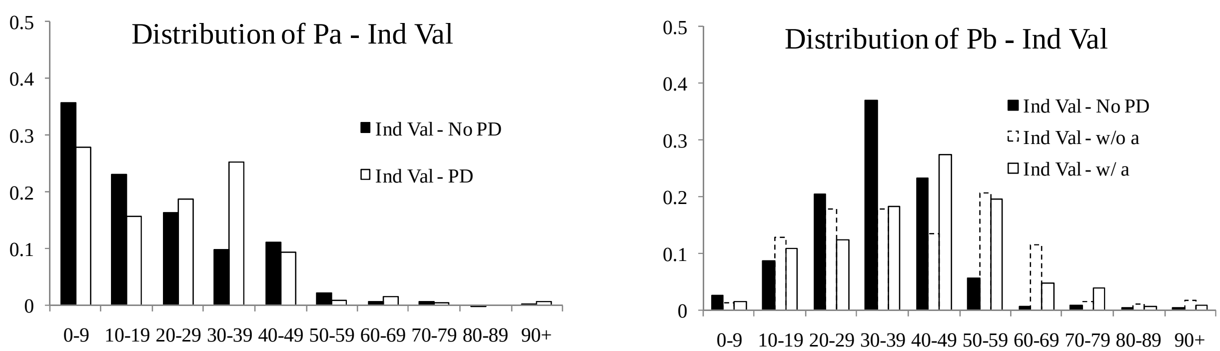
The results are presented separately for each of the three market conditions (independently valued goods, complementary goods, and positively correlated goods). For each condition a series of five results are presented.

1. The impact of the ability to sequentially price discriminate on the price of good A.
2. The impact of the ability to sequentially price discriminate on the price of good B.
3. The impact that comparison shopping has on the price for good A.
4. The impact that comparison shopping has on the price for good B.
5. The welfare implications (buyer surplus and seller profit) of the ability to engage in price discrimination.

4.2.1 *The Case of Independent Values*

Figure 2 shows the distribution of prices for good A (left panel) and good B (right panel). Not surprisingly, good A prices tend to be much lower than good B prices, as sellers are competing for customers via good A prices.

Figure 2. Distribution of Prices in Independent Value Treatments



Impact on price of good A: The ability to sequentially price discriminate leads to nominally but not significantly greater prices (α_1=0).

Support: The top portion of Table 3 provides the econometric support based upon the linear mixed effects model estimation.

[9] 500 periods per seller × 4 sellers per session × 4 sessions per treatment × 6 treatments = 48,000 market decision periods. The last 500 periods of each session are used to control for learning effects.

The average price of good A is only 18 when sellers cannot base the price of good B on the good A purchase decision. This amount nominally increases to 21.6 when sellers do have the ability to set conditional prices for good B. In both cases, competition has forced the price of good A to be low and in fact it is not uncommon to see sellers setting a price of 0 for good A in both treatments.

With independent values, sellers gain no information about the consumer's valuation of good B based upon the decision to purchase good A. Therefore, one would expect there to be no difference between the price for someone who did buy A and the price for someone who did not. Further, these prices should equal that observed when sellers cannot discriminate. Given the parameters used in the experiments, the optimal price of good B should be 50 for all buyers in independent values conditions.

Table 3. Linear Mixed Effects Estimation for
Average Prices in "Independent Values" Treatment

Model: $Pa_{ijt} = \alpha_0 + \alpha_1 PD_j + \varepsilon_i + \varepsilon_j + \varepsilon_{ijt}$

	Intercept	PD
estimate	18.0	3.6
t-statistic	6.23	0.88
p-value	<0.01	0.41

Model: $Pb_{ijt} = \beta_0 + \beta_1 PD_j \times BoughtA + \beta_2 PD_j \times (1-BoughtA) + \varepsilon_i + \varepsilon_j + \varepsilon_{ijt}$

	Intercept	PD×BoughtA	PD×(1-BoughtA)
estimate	33.2	6.3	6.1
t-statistic	8.28	1.11	1.09
p-value	<0.01	0.27	0.28

The unit of observation is at the individual level each period. Each session and period is modeled as having a random effect while the treatments are modeled as a fixed effect. PD is a dummy variable that equals 1 if the seller was operating in a market in which price discrimination was possible and 0 otherwise. BoughtA is a dummy variable that equaled 1 if the price was targeted to people who had purchased good A and 0 otherwise.

Impact on the price of Good B: As expected, sellers do not set different prices for buyers based upon the decision to purchase good A. The ability to engage in sequential price discrimination leads to nominally, but not significantly, higher prices for good B.

Support: The lower section of Table 3 provides the econometric support. The lack of a difference for those who did and those who did not buy good A is based upon a test of the hypotheses that $\beta_1=\beta_2$, which cannot be rejected at standard levels. That the ability to set prices sequentially does not impact the price of good B is evidenced by the lack of significance on β_1 and β_2. One must reject the hypothesis that sellers set the optimal price for good B when sellers cannot price discriminate (i.e. $\beta_0=50$) at all standard levels of significance. However, one would not reject the hypothesis that the average price is 50 for either segment when sellers can price discriminate at the 5% significance level (i.e. $\beta_0 + \beta_1 = 50$

and $\beta_0 + \beta_2 = 50$). Of course, the prediction for good B price is for every seller to charge 50 in every period, which does not occur as evidenced by the right hand panel of Figure 2.

The next two findings evaluate the impact that comparison shopping has on consumers. Since the best price for good A that comparison shoppers observe is the minimum of four prices, whereas uninformed buyers observe a single price drawn from the same distribution, comparison shoppers must have weakly lower prices. The amount by which comparison shopping lowers the expected price for good A relative to what an uninformed buyer would pay is a function of the variance within a market period. Ultimately, there is considerable variation within a market resulting in large gains from comparison shopping.[10]

Impact of Comparison Shopping on Price for Good A: Comparison shopping lowers the price of good A by 66% when sellers cannot price discriminate and 50% when they can.

Support: Table 4 provides the estimation results for linear mixed effects models for the minimum good A price. The results in Table 3 identify the typical price paid by uninformed consumers.

Table 4. Linear Mixed Effects Estimation for
Minimum Price of Good A and Low Price Seller's Good Price in "Independent Values" Treatment

Model: $MinPa_{jt} = \gamma_0 + \gamma_1 PD_j + \varepsilon_j + \varepsilon_{jt}$

	Intercept	PD
estimate	6.1	5.6
t-statistic	1.91	1.24
p-value	0.06	0.22

Model: $Pb|MinPa_{jt} = \omega_0 + \omega_1 PD_j \times BoughtA + \omega_2 PD_j \times (1\text{-}BoughtA) + \varepsilon_j + \varepsilon_{jt}$

	Intercept	PD×BoughtA	PD×(1-BoughtA)
estimate	32.0	5.6	4.8
t-statistic	8.05	0.99	0.86
p-value	<0.01	0.32	0.39

The unit of observation is at the market level each period. Each session and period is modeled as having a random effect, while the treatments are modeled as a fixed effect. PD is a dummy variable that equals 1 if the seller was operating in a market in which price discrimination was possible and 0 otherwise. BoughtA is a dummy variable that equaled 1 if the price was

[10] As the percentage of the customers who comparison shop changes, the distribution used by sellers to set prices will also change. Therefore one cannot predict that the same levels or treatment effects will hold under different search frequencies. See Deck and Wilson (2006) for a discussion of how changes in the percentage of informed customers can change seller behavior in a similar market experiment.

targeted to people who had purchased good A and 0 otherwise.

Unlike good A purchases for which comparison shoppers consider the lowest of four prices, comparison shoppers only observe the good B price for the seller who offered the lowest good A price. These consumers could fare worse than typical uninformed customers if sellers who set the lowest price for good A systematically charge higher prices for good B.

Impact of Comparison Shopping on Price for Good B: Sellers who set the lowest prices for good A do not charge substantially different prices for good B as compared to other sellers.

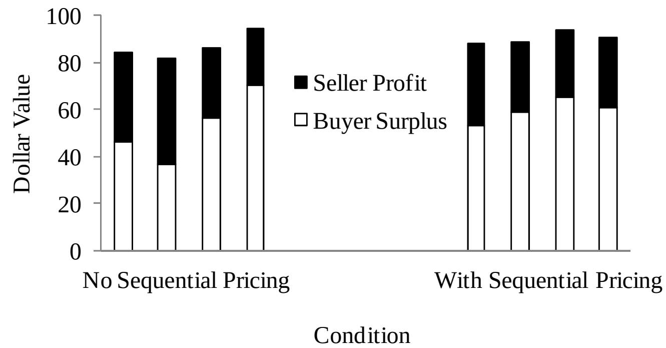
Support: Table 4 also provides the estimation result for the linear mixed effect model for the price of Good B charged by sellers who set the lowest price for good A. This is comparable to results in Table 3 for the typical uninformed consumer.

The final result in this subsection focuses on the welfare implications of the ability to price discriminate. Buyer (consumer) surplus is the difference between the buyer's value for the item and the price actually paid. Seller profit is the difference between the price received and the item's cost (here normalized to C=0). Efficiency is the percentage of possible gains from trade (consumer surplus + seller profit) that are actually realized. In this market maximum efficiency is obtained when every buyer purchases both goods. While this will occur if the price of both goods is 0, the sellers would earn no profit at this price. Ultimately, these markets were highly efficient, averaging 84% without the ability to price discriminate and 79% with sequential pricing, an insignificant difference. Further, the ability to sequentially price did not change buyer surplus or seller profit as made explicit in the following finding.

Welfare Implications of Sequential Price Discrimination: Sellers' ability to sequentially price discriminate does not change the welfare outcomes in these markets.

Support: Figure 3 plots buyer surplus and seller profit for each session in the two independent values conditions. Using the session average as the unit of measure, one cannot reject the null hypothesis of no treatment effect on buyer surplus, seller profit, or efficiency based upon the Wilcoxon Rank Sum test.

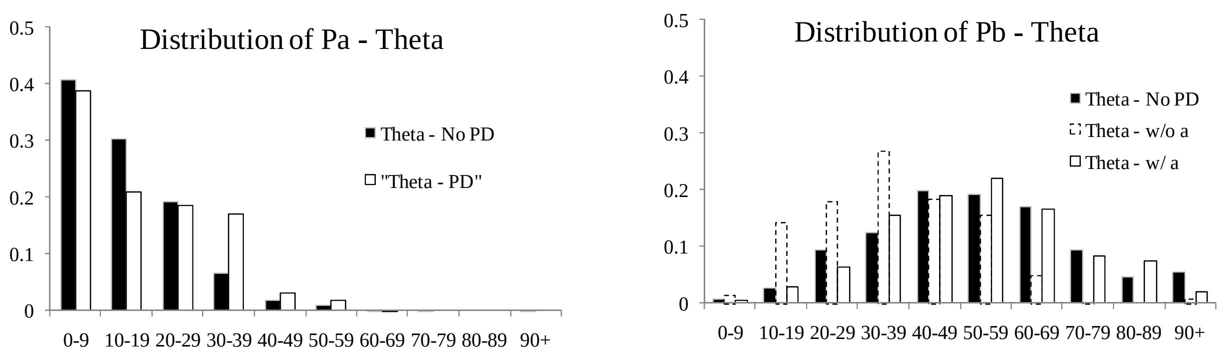
Figure 3. Welfare Implications of Sequential Pricing with Independent Values



4.2.2 *The Case of Complementary Goods*

The analysis of complementary goods closely parallels the analysis of the independent values case. Figure 4 shows the distribution of prices for each good by condition. Evident from the figure is that the price of good A tends to be higher when sellers can sequentially price discriminate, although this difference is not significant. Also evident is the result that buyers who purchased good A paid significantly more for good B than those who did not buy good A when sellers could price discriminate. This effect is consistent with the model since purchasing good A increases the marginal value of good B. Interestingly, the distribution of the price of good B when sellers cannot conditionally price is similar to the distribution of prices for customers who could be identified as having purchased good A. That is, rather than the practice of price discrimination leading to higher prices for the high valued buyers, it actually leads to a price discount for the low value segment. These results are formalized in the next two findings

Figure 4. Distribution of Prices in Complementary Goods Treatments



Impact on price of good A: The ability to sequentially price discriminate leads to nominally but not significantly greater prices.

Support: The top portion of Table 5 provides the econometric support based upon the linear mixed effects model estimation (α_1=0).

Impact on the Price of Good B: As expected, sellers set greater prices for buyers who purchased good A than those that did not when sellers could set conditional prices. When unable to discriminate, sellers set prices similar to those set for buyers who could be identified as having purchased good A.

Support: The lower portion of Table 5 provides the econometric support. The difference in price for those who did and those who did not purchase good A when sellers could price discriminate is based upon a test of the null hypotheses that H_o: $\beta_2 - \beta_1 = 0$ against the one sided alternative that $\beta_2 - \beta_1 > 0$. The second claim is supported by the lack of significance for β_1.

Table 5. Linear Mixed Effects Estimation for
Average Prices in "Complements" Treatment

Model: $Pa_{ijt} = \alpha_0 + \alpha_1 PD_j + \varepsilon_i + \varepsilon_j + \varepsilon_{ijt}$

	Intercept	PD
estimate	13.0	3.4
t-statistic	5.33	0.98
p-value	<0.01	0.37

Model: $Pb_{ijt} = \beta_0 + \beta_1 PD_i{\times}BoughtA + \beta_2 PD_j{\times}(1\text{-}BoughtA) + \varepsilon_i + \varepsilon_j + \varepsilon_{ijt}$

	Intercept	PD×BoughtA	PD×(1-BoughtA)
estimate	51.8	-1.0	-17.7
t-statistic	10.80	-0.14	-2.60
p-value	<0.01	0.89	<0.01

The unit of observation is at the individual level each period. Each session and period is modeled as having a random effect while the treatments are modeled as a fixed effect. PD is a dummy variable that equals 1 if the seller was operating in a market in which price discrimination was possible and 0 otherwise. BoughtA is a dummy variable that equaled 1 if the price was targeted to people who had purchased good A and 0 otherwise.

As in the case of independent values, comparison shopping leads to a dramatic reduction in the price that a buyer considers given the within period variation in prices. Also, sellers who set the lowest price for good A do not charge substantially different prices for good B as compared to the other sellers in the market.

Impact of Comparison Shopping on Price for Good A: Comparison shopping lowers the price of good A by 62% when sellers cannot price discriminate and 50% when they can.

Support: Table 6 provides the estimation results for linear mixed effects models for the minimum good A price. The results in Table 5 identify the typical price paid by uninformed consumers.

Impact of Comparison Shopping on Price for Good B: Sellers who set the lowest prices for good A do not charge substantially different prices for good B as compared to other sellers.

Support: Table 6 also provides the estimation results for the linear mixed effect model for the price of good B charged by sellers who set the lowest price for good A. These are comparable to results in Table 5 for the typical uninformed consumer.

Table 6. Linear Mixed Effects Estimation for
Minimum Price of Good A and Low Price Seller's Good Price in "Complements" Treatment

Model: $MinPa_{jt} = \gamma_0 + \gamma_1 PD_j + \varepsilon_j + \varepsilon_{jt}$

	Intercept	PD
estimate	5.4	3.7
t-statistic	2.29	1.11
p-value	0.02	0.27

Model: $Pb|MinPa_{jt} = \omega_0 + \omega_1 PD_j \times BoughtA + \omega_2 PD_j \times (1\text{-}BoughtA) + \varepsilon_j + \varepsilon_{jt}$

	Intercept	PD×BoughtA	PD×(1-BoughtA)
estimate	53.4	-0.5	-19.6
t-statistic	8.80	-0.05	-2.28
p-value	<0.01	0.96	0.02

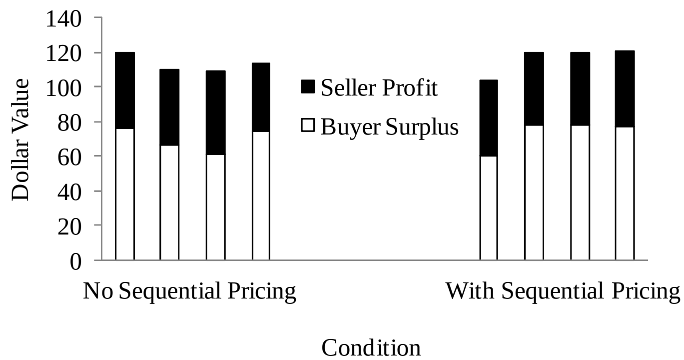
The unit of observation is at the market level each period. Each session and period is modeled as having a random effect while the treatments are modeled as a fixed effect. PD is a dummy variable that equals 1 if the seller was operating in a market in which price discrimination was possible and 0 otherwise. BoughtA is a dummy variable that equaled 1 if the price was targeted to people who had purchased good A and 0 otherwise.

The analysis now turns to the welfare implications of the ability to price discriminate with conditional pricing. Ultimately, the practice does not significantly impact buyer surplus, seller profit, or efficiency. This result seems surprising in light of the fact that the practice of sequential pricing leads to lower good B prices for some buyers. However, the good A prices are so low due to the competition that the percentage of buyers who do not purchase good A is relatively small and the surplus lost when these buyers do not purchase good A is necessarily small since they have low valuation for the good.

Welfare Implications of Sequential Price Discrimination: Sellers' ability to sequentially price items does not change the welfare outcomes in these markets.

Support: Figure 5 plots buyer surplus and seller profit for each session in the two complementary goods conditions.[11] Using the session average as the unit of measure, one cannot reject the null hypothesis of no treatment effect on buyer surplus, seller profit, or efficiency based upon the Wilcoxon Rank Sum test.

Figure 5. Welfare Implications of Sequential Pricing with Complementary Goods

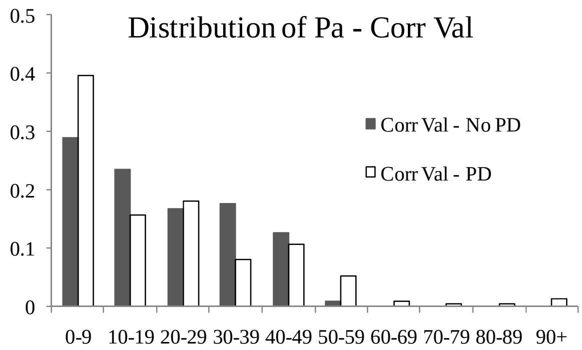


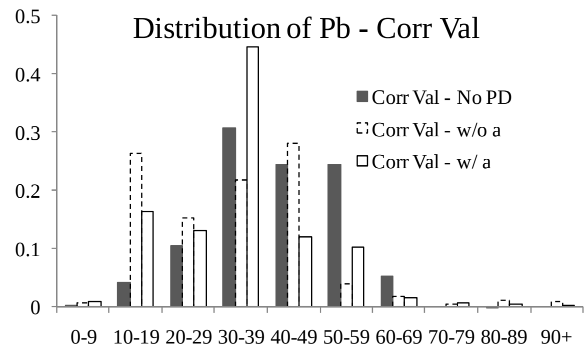
4.2.3 *The Case of Correlated Values*

The analysis of this subsection closely parallels the two previous subsections. Figure 6 plots the distribution of prices in the correlated values treatments.

Figure 6. Distribution of Prices in Correlated Values Treatments

[11] For making comparisons across value conditions it is important to keep in mind that the total surplus possible is greater with complementary goods than with either of the other conditions. With independent values and with correlated values the average potential surplus is 100 whereas it is 130 = 100 × θ for the complementary goods case. Hence it is possible for both buyer surplus and seller profits to be higher in this condition than in the other two, which is in fact what occurred.





Impact on Price of Good A: The ability to sequentially price discriminate has no impact on the average price of good A (α_1=0).

Support: The top portion of Table 7 provides the econometric support based upon the linear mixed effects model estimation.

Impact on the Price of Good B: The average posted price when sellers cannot discriminate based upon who purchased good A was statistically the same as the average price posted to buyers who could be identified as having purchased good A. Buyers who could be identified as not having purchased good A were quoted a (marginally) significant lower price for good A than those buyers whose decision could not be identified by a seller, as predicted. However, contrary to the predictions, there is no statistical difference between the prices paid by those who had and those who had not bought good A when sellers could discriminate.

Support: The lower portion of Table 7 provides the econometric support. The claim that the price quoted to buyers in the absence of conditional pricing is the same as the price quoted to buyers who purchased good A when sellers could discriminate is supported by the lack of significance for β_2. The marginal price break for those identified as not purchasing good A relative to the no price discrimination case is evidenced by the marginal significance of β_1 in a one sided test with H_a: $\beta_1 < 0$. The result that there is no difference between the price for those who did and those who did not purchase good A when sellers could discriminate is based upon a test of $\beta_1 = \beta_2$.

Table 7. Linear Mixed Effects Estimation for
Average Prices in "Correlated Values" Treatment

Model: $Pa_{ijt} = \alpha_0 + \alpha_1 PD_j + \varepsilon_i + \varepsilon_j + \varepsilon_{ijt}$

	Intercept	PD
estimate	19.7	-0.3
t-statistic	4.32	-0.05
p-value	<0.01	0.96

Model: $Pb_{ijt} = \beta_0 + \beta_1 PD_i \times BoughtA + \beta_2 PD_j \times (1\text{-}BoughtA) + \varepsilon_i + \varepsilon_j + \varepsilon_{ijt}$			
	Intercept	PD×BoughtA	PD×(1-BoughtA)
estimate	39.5	-6.4	-7.7
t-statistic	10.15	-1.17	-1.40
p-value	<0.01	0.24	0.16

The unit of observation is at the individual level each period. Each session and period is modeled as having a random effect while the treatments are modeled as a fixed effect. PD is a dummy variable that equals 1 if the seller was operating in a market in which price discrimination was possible and 0 otherwise. BoughtA is a dummy variable that equaled 1 if the price was targeted to people who had purchased good A and 0 otherwise.

As in the two previous cases, comparison shopping leads to substantially lower prices for good A due to the high within period price variation and that the sellers charging the lowest price do not charge different prices for good as compared to their rivals.

Impact of Comparison Shopping on Price for Good A: Comparison shopping lowers the price of good A by about 44% when sellers cannot price discriminate and 65% when they can.

Support: Table 8 provides the estimation results for linear mixed effects models for the minimum good A price. The results in Table 7 identify the typical price paid by uninformed consumers.

Table 8. Linear Mixed Effects Estimation for
Minimum Price of Good A and Low Price Seller's Good Price in "Correlated Values" Treatment

Model: $MinPa_{jt} = \gamma_0 + \gamma_1 PD_j + \varepsilon_j + \varepsilon_{jt}$			
	Intercept	PD	
estimate	11.1	-2.5	
t-statistic	3.19	-0.50	
p-value	<0.01	0.61	

Model: $Pb/MinPa_{jt} = \omega_0 + \omega_1 PD_j \times BoughtA + \omega_2 PD_j \times (1\text{-}BoughtA) + \varepsilon_j + \varepsilon_{jt}$			
	Intercept	PD×BoughtA	PD×(1-BoughtA)
estimate	38.4	-5.1	-8.4
t-statistic	9.32	-0.88	-1.44
p-value	<0.01	0.38	0.15

The unit of observation is at the market level each period. Each session and period is modeled as having a random effect while the treatments are modeled as a fixed effect. PD is a dummy variable that equals 1 if the seller was operating in a market in which price discrimination was possible and 0 otherwise. BoughtA is a dummy variable that equaled 1 if the price was targeted to people who had purchased good A and 0 otherwise.

Impact of Comparison Shopping on Price for Good B: Sellers who set the lowest prices for good A do not charge substantially different prices for good B as compared to other sellers.

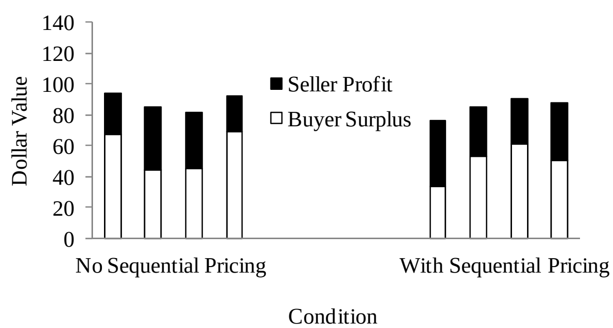
Support: Table 8 also provides the estimation results for the linear mixed effect model for the price of good B charged by sellers who set the lowest price for good A. These are comparable to the results in Table 6 for the typical uninformed consumer.

With correlated values there are no adverse welfare implications due to sequential pricing, just as in the two previous cases.

Welfare Implications of Sequential Pricing: Sellers' ability to sequentially price items does not change the welfare outcomes in these markets.

Support: Figure 7 plots buyer surplus and seller profit for each session in the two correlated values conditions. Using the session average as the unit of measure, one cannot reject the null hypothesis of no treatment effect on buyer surplus, seller profit, or efficiency based upon the Wilcoxon Rank Sum test.

Figure 7. Welfare Implications of Sequential Pricing with Correlated Values



4.3 Comparison of Sequential Pricing with Discrimination and Mixed Bundling in Competitive Markets

As a final point we compare the results here with those of Aloysius and Deck (2008) for mixed bundling using a similar framework, subject pool, subject interface, and parameterizations. The overall efficiency is substantially lower when sellers are engaging in sequential pricing with discrimination as opposed to mixed bundling. This efficiency loss is significant for the case of independent values and marginally significant for the cases of complements and positively correlated goods (based upon a Wilcoxon Rank Sum comparing the session level efficiencies; W=25, 22, and 22 respectively). This result is driven in part because sequential pricing precludes price competition for the second good. The structure of the competition is also such that comparison shoppers with low values for good A do not purchase good B even if they have a high value for it, which also lowers efficiency. For sellers, the lost revenue from buyers who never visit any store due to a low value for good A is more than offset by the increased profits from those who continue to visit. Specifically, the average profit of the sellers in each of the 24 sequential pricing sessions was greater than the average profit from any bundling session reported in Aloysius and Deck (2008). Formally, the average within session profits are statistically higher in the independent values, complements, and positively correlated values conditions with sequential price discrimination than with bundling (Wilcoxon Rank Sum Statistic W=26 for all three comparisons). The implication is that sequential pricing could be more harmful to the consumer than bundling.

5. Conclusions

New technologies will enable sellers to engage in new pricing strategies and it is important to anticipate how these strategies are likely to affect sellers and customers. Currently, there is a growing trend in retail markets to track individual items. RFID tags or similar technologies can be used to identify which items a buyer intends to purchase at a given price, just as placing an item in an electronic shopping cart does for an e-tailer. Currently, sellers openly use this information to manage inventory and make recommendations regarding other products. However, this information could also be used to adjust prices for other items.

What are the likely implications of sellers being able to set prices sequentially and discriminate based upon previous actions? As a first step, this paper presents a theoretical model that can be used to answer this question for monopoly markets. The results indicate that the ability to set prices sequentially, absent the ability to discriminate, increases profits relative to a pure components framework where the monopolist sets a price for each good simultaneously when the goods are substitutes. Further, sequential pricing with discrimination is more profitable than mixed bundling when the goods are either close substitutes or when the goods are highly positively correlated.

The technology to engage in sequential pricing exists in competitive markets too and the implications may be very different. Theoretically, the related concept of bundling has been shown to be an effective method of extracting surplus in monopoly markets. However, Foubert and Gisbrecht (2007) find that contrary to intuition, promotional bundles are far more useful at inducing switching brands than at boosting category sales. Aloysius and Deck (2008) show that sellers use bundling as a competitive weapon rather than a tool for extracting surplus. Therefore, this paper reports a series of experiments designed to explore sequential pricing in competitive markets. The results indicate the ability to set conditional sequential prices does not impact social welfare or harm consumers. It does however shift some of the benefits between those who comparison shop and those who do not depending on the underlying relationship of the goods. The ability to price discriminate does not impact the price of the item initially offered for sale, but does impact the price of the second item depending on the underlying structure of the goods. When the goods are complements, those who are identified as not having purchased the first good receive a substantial price discount. When a buyer's values for the two goods are highly correlated, those who could be identified as having not bought the initial good received a lower price than they would have if they could not have been identified. A comparison of the current results with those reported previously for bundling indicate that sequential pricing with discrimination increases seller profits, but lowers efficiency, indicating that the practice may be relatively harmful to consumers. However, it remains to be seen what would occur in a market where sellers are able to endogenously decide what prices to post and advertise initially (as with bundling) and what prices to withhold (as with sequential pricing) as will be the case in the naturally occurring market place. More generally this research is meant to be forward looking, generating questions to spur further research into how technological advances are likely to impact market behavior.

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Experiment Instructions

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

You are a seller.
In today's experiment you are a seller and so are the other three participants in the experiment. Each seller has two types of goods; good A and good B. You and the other three sellers can set your price for good A, price for good B only, and price for good B with A. That is, you can charge a different price for good B depending on whether or not Good A is purchased. Sellers do not incur any cost to produce the goods and thus profit equals the selling price if a sell is made.

If I am selling, who is buying?
Buyers are automated by the computer. Every **3** seconds a new potential buyer comes to the market. The buyer's values for goods A and B are each drawn randomly from [0,1,2,...,99,100], but there is a restriction that | value for good A - value for good B | $\leq$ 50. This means that the buyer's value for good A cannot be too different from the buyer's value for good B. Therefore, if a buyer has a low value for good A then the buyer is likely to have a low value for good B as well and vice versa. That is, buyer values are positively correlated.

The buyer's value of buying both goods equals the value of good A + value of good B. *So for example, if the buyer's value of good A is 30 and the buyer's value of good B is 70, the buyer's value of buying both goods is (30+70) = 100. Notice that |30-70|=40 $\leq$ 50.*
There will a large table at the bottom left of your screen that provides all of the information regarding buyer values. The row heading gives the possible buyer values for good A. The column heading gives you the possible buyer values for good B. The numbers in the table give you the possible buyer values of the buying both goods. As stated above, each period the buyer's values will be randomly selected from one cell in this table.

What the potential buyers do.
20% of buyers will visit all four sellers, while the remaining 8**0%** randomly determine which one seller to visit. Therefore **20%** of buyers will only visit you, **20%** will visit you and the three other sellers and **60%** will not visit you at all.

A buyer will first decide to buy Good A or not. If the buyer visits only one seller, then the buyer will purchase Good A if the *price of good A* is less than or equal to the buyer's value of A. If the buyer visits all four sellers, then the buyer will purchase Good A from the seller offering the lowest *price of good A* if that price is not greater than the buyer's value for Good A. All ties between sellers are broken randomly.

A buyer who bought Good A will then consider buying Good B from that same seller and will make a purchase if the *price for good B with A* is not greater than the additional value the buyer would receive from also having good B. A buyer who visits only one seller and does not purchase A will consider buying Good B from that same seller but not the other sellers and will purchase Good B if the *price of good B only* is less than the buyer's value of Good B. A buyer who visits all four sellers, but does not buy good A from anyone will not buy good B regardless of price. Notice that your *price for good B only* and your *price for good B with A* will not impact whether or not a buyer will consider buying Good B from you although these prices will impact the ultimate decision to buy Good B.

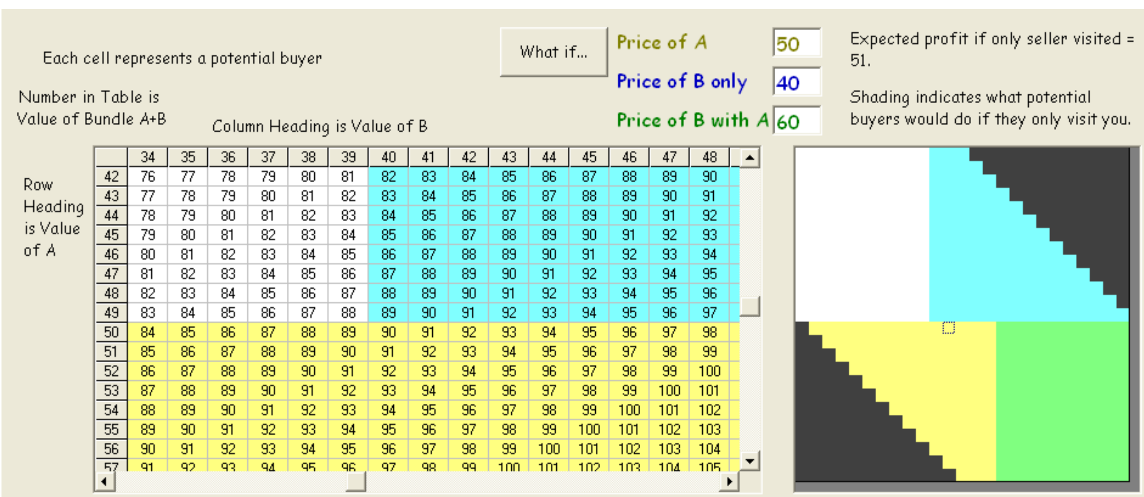
Continuing the example from before, suppose you set price of good A = 50, price of good B only = 60, and price of Good B with A = 25. What would a buyer who only visited you do? With a value of Good A of 30 the buyer would not purchase Good A at a price of good A = 50. Since the buyer's value for Good B is 70, which is greater than the price of price of good B only = 60, the buyer would purchase Good B only. Your profit would be 60.

Had your prices been price of good A = 30, price of good B only = 60, and price of Good B with A = 25 the buyer would have purchased good A (note that a buyer will purchase if the price is less than or equal to the buyer's value). The buyer's additional value from buying Good B is 70 which is greater than or equal to your price of Good B with A = 25 and therefore the buyer would purchase Good B too. Your profit would be 30+25 =55.

"What if" Pricing Tool

The bottom half of your screen (which is shown below) provides a tool that allows you to see what would happen if a buyer were to visit only you. You can specify prices by typing in the three boxes on this portion of your screen. To use the tool you press the "What if..." button. The table in the lower right will shade yellow the region of buyers who will buy good A only, shade blue the region of buyers who will buy good B only, and shade green the region of buyers who will buy both Good A and Good B. The region that is white represents buyers who would not buy anything given your prices. Buyer values cannot be drawn from the region that is black.

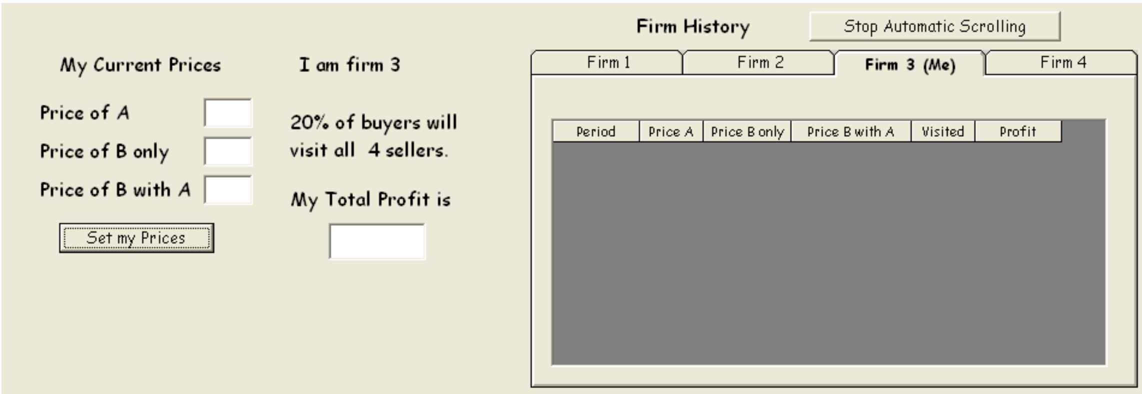
The table on the left is also color-coded. Clicking on a cell in the right table will cause the left table to zoom in on that area. The two tables present the same information; the right table is zoomed out so you can see all potential buyers and the left table is zoomed in so you can see the values of each potential buyer that could be randomly selected.



The expected profit (meaning the average profit you would make if lots and lots of buyer values were randomly drawn) is given on your screen as well. Please note that this information is based upon the assumption that you are the only seller visited, but some buyers visit every seller and some buyers will only visit one of the other sellers.

During the experiment you can update your prices by typing the prices you want to charge in these three boxes and pressing "Update my Prices."

Feedback During Market Session



An example of the top half of the screen is shown above. The top right of your screen gives you all of the information from the market under the heading "Firm History." For each seller you can see price for good A only, price for good B only, and the price for the Good B with A. You can also see if the seller was visited and what profit if any the seller made. The information for each seller is on a separate tab. This information is updated every 3 seconds as a new potential buyer enters the market. The default setting is that the table will automatically scroll down as new information appears, but you can stop scrolling by pressing the "Stop Automatic Scrolling" button and restart it by pressing the button again.

Your firm number will be displayed on the top left of your screen and "(Me)" will appear next to your firm number on the Firm History area. *The example screen above is for Firm 3.* The top left of your screen also shows your current total payoff, which you will be paid at the end of the experiment. Your firm's profit are converted into $US at the rate of 400 in profit = $1.

Your current prices are also displayed in the top left portion of your screen as well. You will enter your initial prices here and press "Set my Prices" but once you set your prices, the only way you can change them is with the "Update my Prices" button on the bottom portion of your screen.

If you have any questions, please raise your hand. Remember that you are paid based upon your decisions and the decisions of others so it is important that you understand the directions completely. If you do not have any questions, please press the "Enter Name" button. Your name will not be recorded, but we will use it to call you to receive your payment in private at the end of the experiment so please enter your first and last name. After you enter your name, please wait silently for further directions.

After you have completed the directions, please answer the following questions (front and back of this page). This will not affect your payoff, but it is designed to make sure that everyone understands the experiment before we begin. If at any point you have a question, please raise your hand and an experimenter will approach you. Once you have completed this sheet an experimenter will check your answers.

<u>Example 1</u>

The randomly determined buyer has
Value of Good A = 30
Value of Good B = 40
Value of Goods A+B = _______

Firm 1 sets the following prices:
Price of Good A = 45
Price of Good B only = 55
Price of Good B with A = 50

If the buyer only visits Firm 1, will the buyer purchase Good A? ________
If the buyer only visits Firm 1, will the buyer purchase Good B? ________
What will Firm 1's profit be? __________ (The 3 other firms will each earn 0 profit.)

<u>Example 2</u>

The randomly determined buyer has
Value of Good A = 60
Value of Good B = 40
Value of Goods A+B = _______

Firm 2 sets the following prices:
Price of Good A = 60
Price of Good B only = 80
Price of Good B with A = 20

If the buyer only visits Firm2, will the buyer purchase Good A? ________
If the buyer only visits Firm 2, will the buyer purchase Good B? ________
What will Firm 2's profit be? __________ (The 3 other firms will each earn 0 profit.)

<u>Example 3</u>

The randomly determined buyer has
Value of Good A = 60
Value of Good B = 40
Value of Goods A+B = _______

Firm 3 sets the following prices:
Price of Good A = 60
Price of Good B only = 20
Price of Good B with A = 80

If the buyer only visits Firm 3, will the buyer purchase Good A? ________
If the buyer only visits Firm 3, will the buyer purchase Good B? ________
What will Firm 3's profit be? __________ (The 3 other firms will each earn 0 profit.)

<u>Example 4</u>

The randomly determined buyer has
Value of Good A = 50
Value of Good B = 40
Value of Goods A+B = _______

Firm 4 sets the following prices:
Price of Good A = 50
Price of Good B only = 40
Price of Good B with A = 40

If the buyer only visits Firm 4, will the buyer purchase Good A? ________
If the buyer only visits Firm 4, will the buyer purchase Good B? ________
What will Firm 's profit be? __________ (The 3 other firms will each earn 0 profit.)

Example 5

The randomly determined buyer has
Value of Good A = 70
Value of Good B = 30
Value of Goods A+B = _______

Firm 1 sets the following prices:
Price of Good A = 80
Price of Good B only = 25
Price of Good B with A = 15

Firm 2 sets the following prices:
Price of Good A = 60
Price of Good B only = 20
Price of Good B with A = 50

Firm 3 sets the following prices:
Price of Good A = 60
Price of Good B only = 60
Price of Good B with A = 60

Firm 4 sets the following prices:
Price of Good A = 45
Price of Good B only = 55
Price of Good B with A = 45

If the buyer visits all four sellers, then
Firm 1's profit = _______
Firm 2's profit = _______
Firm 3's profit = _______
Firm 4's profit = _______