Price Bundling in Competitive Markets

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This research investigates mixed bundling pricing in oligopoly markets with both comparison and uninformed shoppers. We examine how additivity and correlation of multi-product customer values, influence single item and bundle prices. We characterize the mixed strategy equilibrium and for specific parameters we compute undominated pricing strategies. We also conduct two sets of controlled laboratory experiments with human decision makers, focusing on additivity and on correlation. Across all conditions sellers display a systematic bias by overemphasizing comparison shoppers. The markets are highly efficient with low pricing for both buyer-types. Thus, competitive pressure seems to reduce the exploitative properties of monopolist bundling.

KEYWORDS
Mixed Bundling, Comparison Shopping in Electronic Markets, Multi-Dimensional Buyer Values, Laboratory Experiments
1. INTRODUCTION

The well-known “Beer and Diapers” parable, which has some factual basis (Whitehorn 2006), illustrates the unintuitive nature of customer product values (or maximum willingness to pay) that may be exploited by price setting brand managers. As advances in technology give firms more granular and immediate data to be mined for information on customer preferences (see McCarty and Hastak 2007 for examples), this information enables retailers to develop more accurate descriptions of how a potential customer's values for multiple products are related. However, to optimally leverage this information it is necessary to understand how knowledge of buyer preferences interacts with the competitive pressures faced by firms selling multiple items. From the early advent of business computing systems, researchers (e.g., Bonczek et al., 1981) have recognized the need to understand the entire process of decision making in order to effectively integrate technology-based systems. Pricing decisions while facilitated by decision support systems (Hart 2007) in the retail industry are still largely made by managers (Diaz 2006). Human decision makers are subject to biases and there is evidence that professional managers are not immune (see for example March and Shapira 1987).

A prevalent multi-product strategic marketing tool is mixed bundling, where retailers products both individually and as part of a bundle. Be it consumer packaged goods (a shrink wrapped package of shampoo and conditioner), consumer durables (computers and printers) or services (cable TV and internet), firms can use bundling to improve measures of performance including profits and market share. Academic researchers are increasingly gaining a better understanding of optimal pricing strategies and the environment in which these strategies may be effectively deployed (Guiltinan 1987, Simon and Dolan 1998, Estelami 1999, Noble and Gruca 1999, Barua and Chellappa 2002). However, Stremersch and Tellis (2002) survey marketing, law, and economics literatures on bundling and make three primary observations which remain relevant despite much subsequent research. First, the literature has focused primarily on profit maximization by a monopolist. Second, one of the most promising areas of further research is the impact of competitive bundling strategies and third, conditions for optimality still remains an open question, one they posit will depend upon the distribution of customer valuations.

This paper looks at the impact that market competition has on pricing and profitability when retailers engage in mixed bundling as a function of the inter-product relationship of buyer values. Specifically, we investigate two types of buyer value relationships that might exist between products. In Experiment 1, we consider the degree of complementarity that exists between the products. Following Venkatesh and Kamakura (2003) we consider the degree of additivity in the value of the bundle. For complements the value of the bundle of two different goods exceeds the sum of the values for the individual
items, whereas for substitutes the bundle is worth less than the sum of individual item values. The second inter-product relationship that we consider (Experiment 2) is the degree of correlation of the individual values. Buyer values are positively correlated if buyers who have a high (low) value for one good are more likely to have a high (low) value for the other good, while negatively correlated values would mean that a buyer who has a high value for one good is likely to have a low value for the other. It is important to note that complementarity / substitutability and correlation of values are distinct concepts. Two books can have positively correlated values and be substitutes if they have the same topic and cover the same content, but if they have the same topic and cover different content then buyer values would be positively correlated and the books would be complements. In addition to the four treatment conditions, we also consider a baseline environment where values are independent and additive.

Our markets are structured so that a fraction of buyers comparison shop, while others visit a single retailer à la Varian (1980). Informed buyers, who comparison shop, can be thought of as online shoppers who easily compare prices while uninformed buyers can be viewed as those who visit the local bricks and mortar. Across all five conditions, we find that sellers are overly competitive, often pricing below the support of the mixed strategy equilibrium strategy. While comparison shoppers receive lower prices than uninformed buyers, the uninformed buyers benefit from the competition by paying lower prices. Unlike with monopoly markets, we find little evidence that mixed bundling harms consumers.

2. THEORETICAL MODEL

Previous research has mostly analyzed bundling by monopolists. Customers with a high valuation for a favored product will buy a bundle although they may not pay the standalone price for the unfavored product (Stigler 1968). Mixed bundling (offering separate products and the bundle) can be effective even when the consumer’s valuation for each good is independent and additive (see Adams and Yellen 1976 who introduce the now ubiquitous structure for studying bundling). The general result is that customers with a high degree of asymmetry in product valuations will buy an individual product they favor, while customers with similar values for the products will either buy the bundle or nothing. Schmalensee (1984) finds similar results with continuous (bivariate normal) valuations while McAfee et. al (1989) provide conditions for optimality of bundle pricing. Venkatesh and Kamakura (2003) introduce an additivity parameter to allow for goods to be complements or substitutes. For a more detailed review of the bundling literature see Aloysius et al. (forthcoming).1

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1 This paper is a companion paper to Aloysius et al. (forthcoming). The current paper focuses on mixed bundling with different inter-product valuations. Aloysius et al. (forthcoming) considers a subset of these buyer valuations when comparing
Following Adams and Yellen (1976), Venkatesh and Kamakura (2003), and Aloysius et al. (forthcoming), we develop a model of bundling as a form of price discrimination. In the model, n identical sellers can produce goods A and B at marginal costs $c_A$ and $c_B$. Buyers values for the goods are given by $v_A$ and $v_B$ with values distributed $f(v_A,v_B)$. The value of the bundle is $v_{AB} = (1+\theta) \times (v_A + v_B)$. When $\theta > 0$ the goods are compliments, and when $\theta < 0$ they are substitutes. Buyers demand at most one unit of each good and sellers can set prices $P_A$, $P_B$, and $P_{AB}$ for the single items A and B and the bundle AB, respectively. Sellers cannot monitor a buyer’s purchases; i.e. a seller cannot charge more for the bundle than for individual items, i.e. $P_{AB} \leq P_A + P_B$. If this condition holds with equality, a seller is said to be engaging in pure component pricing.

A novel feature of the model is the notion of informed and uninformed consumers as in Varian (1980) and Deck and Wilson (2006). A fraction 1- $\alpha$ of the customers are assumed to be comparison shoppers fully informed of all prices while the remainder, a fraction $\alpha$, visit a single seller. Any shopper who visits a single seller is assumed to pick randomly among the $n$ rivals. Thus, each of the $n$ sellers expects to act as a monopolist to the proportion $\alpha / n$ of the total number of customers. Importantly, a seller cannot identify if a particular buyer is a comparison shopper or is only visiting the one seller.\(^3\)

The problem faced by an uninformed potential customer with values $v_A$, $v_B$, $v_{AB}$ who observes the prices $P_A^i$, $P_B^i$, and $P_{AB}^i$ from seller $i$ is straightforward. The customer will purchase the bundle AB if $v_{AB} - P_{AB}^i \geq \max (0, v_A - P_A^i, v_B - P_B^i)$. Similar conditions hold for the purchase of A and B separately with the assumption that when more than one choice provides the maximum consumer surplus, the customer will purchase the item or bundle most profitable to the seller.\(^4\) If all customers are uninformed (i.e. $\alpha = 1$), this reverts to the monopoly problem of Venkatesh and Kamakura (2003), who argue there is no general closed form solution.

The informed customer’s problem is more complex but is a logical extension of the uninformed buyer’s problem. The informed customer will purchase the bundle AB from seller $i$ if $v_{AB} - P_{AB}^i > \max (0, v_A - P_A^i, v_B - P_B^i, v_A - P_A^j, v_B - P_B^j, v_{AB} - P_{AB}^j)$, $\forall j \neq i$ with similar conditions holding for purchasing item A or B only. Any tie between sellers is assumed to be broken randomly and, as before, ties within a seller assumed to be resolved in the seller’s favor. That is the informed buyer makes mixed bundling to sequential pricing, a marketing strategy where the seller sets the price of the second good after observing the shoppers buying intention for the first good.

\(^2\) Monitoring refers to situation when the seller can prevent a buyer from purchasing both items separately. When such monitoring is not feasible as is the case in many settings, the equality constraint simply means that the seller cannot charge more for the bundle than the sum of the individual item prices as the buyer could purchase the items individually and create his on bundle. See McAfee, et al. (1989) for discussion of monitoring.

\(^3\) See Deck and Wilson (2006) for theory and experiments regarding tracking customers in a single good market.

\(^4\) If $f(\cdot,\cdot)$ is continuous, a tie occurs on a set of measure 0.
the best decision from the $3n+1$ choices and cannot create a bundle by purchasing components from different sellers.\footnote{Buyer behavior must be individually rational so the buyer has the option to buy nothing resulting in the additional choice beyond the $3n$ options from the $n$ sellers.} If all customers are informed (i.e. $\alpha=0$), this becomes a perfectly competitive market and sellers should compete prices down to cost.

Now consider the problem faced by a seller operating in this market. $1-\alpha + \alpha/n$ of the total customers in this market will observe the seller’s prices (1-$\alpha$ comparison shoppers and $\alpha/n$ that only visit that seller). One option available to the seller is to focus only on the fraction of customers for whom the seller acts as a monopolist given that these buyers only visit that seller. Let $\Pi^m^*$ denote the optimal profit that a monopolist would earn if the entire market was served by a single seller. A seller in market with $n$ sellers and comparison shoppers could guarantee itself an expected profit of $\alpha \Pi^m^*/n$ by mimicking a monopolist and only serving the fraction $\alpha/n$ of the total customers in the market, those that only visit it. This level of guaranteed profit is known as the security profit.

The alternative strategy for the seller is to try to compete with the other $n-1$ sellers for the comparison shoppers. In thinking about the symmetric Nash equilibrium of such a game, it is clear that there are no pure strategy equilibria as a seller would always prefer to slightly undercut its rivals rather than share the comparison shoppers. Thus, any symmetric equilibrium must be in mixed strategies. By similar reasoning there can be no mass points in the equilibrium pricing strategy as the positive probability of a tie would mean that some seller(s) would prefer to deviate. Further, any pure strategy in the support of a mixed strategy equilibrium must generate the same expected payoff given that the other players are following the equilibrium strategy and this payoff cannot be less than the payoff generated by any other strategy available to the player. In this market, sellers always have the option to pursue the security profit $\alpha \Pi^m^*/n$ so any prices that are played in equilibrium must generate that same profit in expectation. In fact, an expression equating the expected profit from following the equilibrium mixing distribution and the security profit implicitly defines the mixed strategy equilibrium distribution.\footnote{The interested reader seeking more details is referred to Aloysius et al. (forthcoming) for more details.}

While solving for the equilibrium mixing distribution is not tractable, for the purposes of this paper, it is sufficient to note that the opportunity to achieve the security profit places identifiable restrictions on the prices that can be supported in equilibrium. Let $\Pi^m^*(P_A, P_B, P_{AB})$ denote the profit that a monopolist would receive if he charged prices $(P_A, P_B, P_{AB})$. Now suppose that a seller in the competitive market set the prices $(P_A, P_B, P_{AB})$. This seller would earn the monopoly profit from a fraction $\alpha/n$ of the customers and would earn that same profit from the fraction $1-\alpha$ of the customers if the seller happened
to be the seller offering a comparison shopper the best deal (in this case comparison shoppers are essentially ignoring the higher priced rivals). Therefore, \((1-\alpha+\alpha/n)\Pi^m(P_A,P_B,P_{AB})\) is an upper bound on the expected profit a seller could earn by charging \((P_A,P_B,P_{AB})\) as the chance that the seller is a comparison shopper’s best deal must be less than or equal to 1. Therefore, if \((1-\alpha+\alpha/n)\Pi^m(P_A,P_B,P_{AB}) \leq \alpha\Pi^m/n\) a seller would never prefer charging \((P_A,P_B,P_{AB})\) to pursuing the security profit. Thus, for \((P_A,P_B,P_{AB})\) to be in the support of the Nash equilibrium mixing distribution it must be that \((1-\alpha+\alpha/n)\Pi^m(P_A,P_B,P_{AB}) > \alpha\Pi^m/n\) or alternatively \(\Pi^m(P_A,P_B,P_{AB}) > (\alpha\Pi^m/n)/(1-\alpha+\alpha/n)\).

3. EXPERIMENTAL DESIGN

We consider a total of five treatments that vary the degree of bundle value additivity (Experiment 1) and the correlation of buyer values between goods (Experiment 2). In our laboratory investigation, we use the following parameter values for the model developed in the previous section: the number of sellers is \(n = 4\); the marginal costs of goods A and B is \(c_A = c_B = 0\); and the proportion of comparison shoppers is \(\alpha = 0.8\) (20% of customers comparison shop and 20% visit each of the 4 sellers individually).\(^7\) We conducted a baseline condition setting \(\theta = 0\) and drawing buyer values independently from \(v_A \sim \text{discrete } U[0,100]\) and \(v_B \sim \text{discrete } U[0,100]\). In this case the goods are neither complements nor substitutes and buyer values are uncorrelated. We denote the baseline condition with B. We also conduct a complements (substitutes) treatment with \(\theta = 0.3\) (-0.3) with the same distribution over single item values. We refer to these treatment as \(\theta^+\) and \(\theta^-\), respectively, and combined with the baseline constitute Experiment 1. In our positively correlated values treatment we hold \(\theta = 0\) and draw values from the joint distribution \(f(v_A,v_B) = \begin{cases} \frac{1}{7651} & \text{if } |v_A - v_B| \leq 50 \\ 0 & \text{else} \end{cases}\) for \(v_A, v_B\) integers \(\in [0,100]\). This generates a correlation of \(\rho = +0.5\) for the values of the two goods; we refer to this treatment as \(V^+\). Our negative correlation treatment, which we denote by \(V^-\) holds \(\theta = 0\) and draws values from the joint distribution \(f(v_A,v_B) = \begin{cases} \frac{1}{7651} & \text{if } 50 \leq |v_A - v_B| \leq 150 \\ 0 & \text{else} \end{cases}\) for \(v_A, v_B\) integers \(\in [0,100]\). This generates a correlation of \(\rho = -0.5\). Treatments \(V^+, V^-\) and B constitute Experiment 2.

\(^7\) Conditioned on a particular seller being visited, there is a 50% chance that the seller is in direct competition for a comparison shopper.
Figure 1 shows the pricing strategies that are not dominated by a seller setting the monopoly prices for each of the conditions in Experiments 1 and 2. That is, the symmetric Nash equilibrium prediction is that all price triples will be contained in the sets identified in Figure 1.

A total of 80 unique participants were drawn from undergraduate business school classes at a state university in the US to serve as sellers. None of the subjects had participated in related experiments. Since buyers in this market demand a single unit of each good and have no incentive not to truthfully reveal their willingness to pay, they were implemented with automated robots, (see Davis and Holt 1993 for a justification of this process). Subjects entered the laboratory and were seated at computers surrounded by privacy dividers, read the directions and completed a handout to verify they understood the experiment.

In total, there were four replications of each of the five treatments including the two new treatments. Sessions lasted for approximately 90 minutes, after which the subjects were paid their seller profit at the rate $\text{Exp 400} = \$\text{US 1}$, where $\text{Exp}$ denotes the experimental currency used to denominate values, costs, and prices. The average of the performance based earnings across all sessions was $18.16 and each subject also received an additional $7.50 show-up payment for participating.

Each session lasted for 750 3-second periods. During each period one robot buyer entered the market drawing a value pair $(v_A, v_B)$ from the given distribution. The robot buyer observed the relevant prices that period depending on whether or not the buyer was a comparison shopper, which was randomly determined. A comparison shopper observed 12 prices (three prices from each of four sellers) while an uninformed buyer only observed three prices (the three prices of a single seller). Given the observed prices, the robot buyer made the purchase that generated the largest buyer surplus (measured as value of purchase minus price paid). If the maximum buyer surplus was negative the buyer did not make any purchase and all ties were broken randomly. The 4 human sellers could observe the prices posted by each rival and any profit realized by a seller. Subject sellers could update their posted prices at any time, with the new prices going into effect in the subsequent period. There was no pause between periods and the subject did not know the number of periods in the experiments. All other parameters and procedures were common information among the sellers.

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8 As discussed above, a strategy cannot be part of the equilibrium mixing distribution if it generates a profit less than $(\alpha \Pi^m/n) / (1 - \alpha + \alpha/n) = .5\Pi^m$.

9 Copies of the directions and handouts are available from the authors upon request.

10 Davis and Korenok (2009) demonstrate that posted offer markets in near continuous time have greater convergence to equilibrium that markets with longer period lengths.
4. RESULTS

The results of each experiment examine three issues: 1) the frequency with which sellers engaged in mixed bundling across treatments, 2) the effect on prices, and 3) the allocation of surplus between buyers and sellers. Before presenting the results we note that in all 5 conditions, on average subject sellers initially set individual prices near 50, which is the expected value of a buyer’s value. Further, in every condition, prices steadily decline over the first portion of the experiment with the trend ending by period 250. Therefore, to control for learning effects we focus on the last 500 periods, similar to the approach of Deck and Wilson (2006) and Aloysius, et al (forthcoming). However, the qualitative results are largely independent of the cutoff.

4.1 Experiment 1 – Manipulating $\theta$

To examine mixed bundling, we define the bundle discount ratio $P_{AB}/(P_A+P_B)$. Pure components has a price ratio of 1 while pure bundling has a price ratio equal to 0.5. To be conservative in estimating the use of mixed bundling we define almost pure components as a ratio greater than or equal to 0.95 and almost pure bundling as a ratio less than or equal to 0.55. Table 1 presents the frequency with which sellers engaged in the various pricing strategies. As evidenced in the table, sellers are overwhelmingly utilizing mixed bundling. However, there is a non-trivial amount of pure bundling occurring and some occurrences of pure component pricing. Having established that sellers overwhelmingly engage in mixed bundling, we turn to the impact of mixed bundling on prices. To control for learning effects when comparing prices, estimation is restricted to the last 500 periods. We present two sets of results for both single item prices and bundle prices: one based upon the average price in a market (the typical price observed by an uninformed buyer) and one based upon the minimum price (the price observed by an informed buyer). The unit of measurement is the average or minimum price in each period in each session. To control for repeated measures within a session, we use a linear mixed effects model that allows for both a treatment fixed effect and a session random effect. The results are in Table 2.

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11 Behavior in B, $\theta^*$ and $V^*$ is also reported in a companion paper, Aloysius et al (forthcoming); however the focus and of the analysis differs between the two papers. The experiments in both papers were developed together and run concurrently.

12 Statistically, there is no difference between the price of good A and B in any treatment. Therefore, we combine the observations of good A and good B prices.
Table 1. Frequency of Pricing Strategy: Additivity

<table>
<thead>
<tr>
<th></th>
<th>Mixed Bundling</th>
<th>Pure Bundling (Almost)</th>
<th>Pure Components (Almost)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta^+ )</td>
<td>84%</td>
<td>12%(21%)</td>
<td>4% (5%)</td>
</tr>
<tr>
<td>B</td>
<td>83%</td>
<td>14%(17%)</td>
<td>3% (6%)</td>
</tr>
<tr>
<td>( \theta^- )</td>
<td>80%</td>
<td>14%(18%)</td>
<td>6% (10%)</td>
</tr>
</tbody>
</table>

Based upon the estimation in Table 2, the average single item price in the baseline is 40.5. The average single item price in \( \theta^+ \) is 40.5 - 1.6 = 38.9 and in \( \theta^- \) is 40.5 - 2.0 = 38.5, neither of which is statistically different from the mean in the baseline. Based upon our results, we conclude that changes in \( \theta \) do not significantly affect the typical market price of the single items. Similar results hold for bundle prices as well as single item and bundle prices for informed buyers.

Table 2. Linear Mixed Effect Estimation for Average / Minimum Prices in Additivity Treatments

<table>
<thead>
<tr>
<th></th>
<th>Mean Prices</th>
<th>Minimum Prices</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Single Item</td>
<td>Bundle</td>
</tr>
<tr>
<td>Constant</td>
<td>40.5*</td>
<td>55.7*</td>
</tr>
<tr>
<td></td>
<td>(12.27)</td>
<td>(8.87)</td>
</tr>
<tr>
<td>PosT</td>
<td>-1.6</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>(-0.33)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>NegT</td>
<td>-2.0</td>
<td>-6.98</td>
</tr>
<tr>
<td></td>
<td>(-0.42)</td>
<td>(-0.79)</td>
</tr>
</tbody>
</table>

Each model is estimated separately. PosT and NegT are dummy variables for the sessions in the \( \theta^+ \) and \( \theta^- \) treatments, respectively. * denotes significant difference at the 5\% level in a two sided t-test. t-statistics are presented in parentheses.

There was great variation in single item and bundle prices, which one would expect if subjects were playing the equilibrium mixing strategy. However, subjects regularly set prices that are dominated by the monopoly strategy and thus should never be played in equilibrium. Furthermore, we define a price triple as being too low if it is not in the undominated set of prices (shown in Figure 1) and if the seller could raise one or more of the prices and enter the undominated set. In the baseline treatment 35\% of price triples set by subjects over the last 500 periods were outside the set indicated in Figure 1; of these 65\% are too low. For complements (\( \theta^+ \)) the percentage of price triples outside the indicated area was 42\% of which 89\% were too low. For substitutes the same pattern emerges: 57\% are outside the region of which 80\% are too low. Clearly the subject sellers in all treatments are overly competitive, focusing too much on comparison shoppers and the prices of
rivals. This tendency is exacerbated in both the superadditive and subadditive conditions relative to the baseline with the new results on subadditivity being the most pronounced.

The low prices observed in the market benefit the consumers. Table 3 provides the percentage of buyers purchasing different items as well as the percentage of those who would be expected to buy those items under monopoly conditions. The observed single item and bundle sales differences between the baseline and the two extreme values of \( \theta \) are significant based upon a Mann-Whitney test that treats the sessions as the unit of observation (test statistic = 26, p-value 0.028). Clearly evident from Table 3 is the result that while bundle purchasers as a percentage of customers increase when goods are complements, they decrease as would be expected, when goods are now substitutes. Also evident from the table is that the changes in bundle sales is offset in both cases by single item sales, not from the percentage of consumers who do not purchase.

<table>
<thead>
<tr>
<th>Table 3. Distribution of Purchase Outcomes in Additivity Treatments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>------------------</td>
</tr>
<tr>
<td>Monopoly Observed:</td>
</tr>
<tr>
<td>Monopoly Observed:</td>
</tr>
<tr>
<td>Monopoly Observed:</td>
</tr>
</tbody>
</table>

Finally, we follow up with an examination of the welfare effects of changes in \( \theta \). Market efficiency is the percentage of potential gains that are actually realized in a market, something that is unobservable in most naturally occurring markets, but readily observable in the laboratory (See Davis and Holt 1993). Figure 2 plots the average efficiency of each session. We find that there is no statistical difference in efficiency with complements or substitutes based upon linear mixed effects estimation, which is omitted for brevity. While overall available surplus is lower when goods are substitutes, efficiency remains relatively unchanged.

4.2 Experiment 2 – Manipulating \( \rho \)

These results are presented in the same order and fashion as those for additivity, so some details are omitted for brevity. Table 4 presents the frequency with which sellers engaged in the various pricing strategies. Again, sellers are overwhelmingly utilizing mixed bundling.
Table 5 provides the treatment effect on observed single item and bundle prices for uninformed and comparison shoppers. While positive correlation ($V^+$) yields individual prices and bundle prices significantly lower than the baseline, our findings suggest that when values are negatively correlated ($V^-$) there are no significant differences from the Baseline.

Table 4. Frequency of Pricing Strategy: Correlation

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Mixed Bundling</th>
<th>Pure Bundling (Almost)</th>
<th>Pure Components (Almost)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V^+$</td>
<td>88%</td>
<td>4% (5%)</td>
<td>8% (10%)</td>
</tr>
<tr>
<td>Baseline</td>
<td>83%</td>
<td>14% (17%)</td>
<td>3% (6%)</td>
</tr>
<tr>
<td>$V^-$</td>
<td>81%</td>
<td>9% (10%)</td>
<td>10% (11%)</td>
</tr>
</tbody>
</table>

Table 5. Linear Mixed Effect Estimation for Average / Minimum Prices in Correlation Treatments

<table>
<thead>
<tr>
<th></th>
<th>Mean Prices</th>
<th>Minimum Prices</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Single Item</td>
<td>Bundle</td>
</tr>
<tr>
<td>Constant</td>
<td>40.9*</td>
<td>56.2*</td>
</tr>
<tr>
<td></td>
<td>(17.09)</td>
<td>(13.01)</td>
</tr>
<tr>
<td>PosT</td>
<td>-8.8*</td>
<td>-10.2</td>
</tr>
<tr>
<td></td>
<td>(-2.61)</td>
<td>(-1.68)</td>
</tr>
<tr>
<td>NegT</td>
<td>-3.6</td>
<td>-0.8</td>
</tr>
<tr>
<td></td>
<td>(-1.05)</td>
<td>(-0.13)</td>
</tr>
<tr>
<td></td>
<td>27.5*</td>
<td>-9.9*</td>
</tr>
<tr>
<td></td>
<td>(7.72)</td>
<td>(-1.95)</td>
</tr>
<tr>
<td></td>
<td>-9.0</td>
<td>(-1.08)</td>
</tr>
<tr>
<td></td>
<td>37.2*</td>
<td>4.0</td>
</tr>
<tr>
<td></td>
<td>(6.31)</td>
<td>(-0.47)</td>
</tr>
</tbody>
</table>

Each model is estimated separately. PosT and NegT are dummy variables that equal 1 if the observation is from a session in which $\rho$ is positive or negative respectively. * denotes significant difference at the 5% level in a two sided t-test. t-statistics are presented in parentheses.

As in the additivity treatments, subjects continue to be too competitive. In $V^+$, 53% of prices were outside the undominated region shown in Figure 1 with 63% being too low. In $V^-$ 67% were outside the undominated region with 58% being too low. This provides further evidence that subject behavior is not consistent with the symmetric mixed strategy Nash equilibrium in these markets.

As before, the relatively low prices observed in the market benefit the consumers. Table 6 compares the observed percentage items bought with that would be expected to buy under monopoly conditions. While differences between the baseline and $V^+$ are not significant, fewer shoppers buy nothing in $V^-$ than in the baseline, a significant difference based upon a Mann Whitney test that treats the session percentage as the unit of measure (test statistic = 26, p-value 0.028). This increase results in a larger percentage of buyers purchasing a single item and not in a larger percentage buying the bundle.
Table 6. Distribution of Purchase Outcomes

<table>
<thead>
<tr>
<th></th>
<th>Buy Nothing</th>
<th>Buy Single Item</th>
<th>Buy Bundle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed:</td>
<td>12%: 33%</td>
<td>21%: 14%</td>
<td>67%: 53%</td>
</tr>
<tr>
<td>Baseline</td>
<td>V⁺</td>
<td>V⁻</td>
<td></td>
</tr>
<tr>
<td>V⁺</td>
<td>13%: 35%</td>
<td>10%: 10%</td>
<td>77%: 51%</td>
</tr>
<tr>
<td>V⁻</td>
<td>4%: 22%</td>
<td>29%: 38%</td>
<td>67%: 66%</td>
</tr>
</tbody>
</table>

Finally, we conclude by examining the welfare implications, which are summarized in Figure 3. While there is no difference between the baseline and the V⁺ condition, we find that the V⁻ condition is more efficient than the Baseline. This is supported through linear mixed effects estimation.¹³

<Insert Figure 3 here>

5. DISCUSSION

Researchers have known for years that bundling can be an effective tool for increasing monopoly sales. This has led to some concerns regarding its anticompetitive pressure. Optimal prices depend on the underlying structure of the value of the two goods, which new technologies and especially the volumes of scanner data that retailers possess will enable marketers to uncover. However, many markets cannot reasonably be described as being controlled by a monopolist. Therefore, it is important to understand how tools such as bundling perform in more competitive markets.

Using controlled laboratory experiments, we consider cases in which goods are complements or substitutes (Experiment 1) or positively or negatively correlated (Experiment 2). In so doing we find a robust pattern in which sellers overwhelmingly engage in mixed bundling. However, rather than facilitating anti-competitive behavior, competition leads to overly competitive prices. These experimental findings may motivate research on potential judgment and decision biases that have these detrimental effects on the effectiveness of pricing by human decision makers. These insights may then enable the design of automated systems and training programs that help improve pricing decisions in various contexts.

In all treatments, comparison shoppers received substantially lower prices than uninformed shoppers. Still seller's emphasis on comparison shoppers helps both types of buyers and this effect may limit the number of comparison shoppers in the market as uninformed people essentially free ride on the pricing effects of those who do comparison shop. Somewhat surprisingly, of the four alternative treatments considered, only the case in which goods were positively correlated led to significantly different prices than the baseline condition.

¹³ Based upon the estimation, average efficiency was 85% in the baseline and the coefficients for V⁺ and V⁻ were 0.01 and 0.07 respectively with two sided p-values of 0.917 and 0.020 respectively. The full table of estimated results is omitted for brevity.
An advantage of the laboratory over naturally occurring data is that we can measure market efficiency using the treatment effects and non-sales. In all cases efficiency, the potential gains from trade that are realized, was high although it was highest when values were negatively correlated. Further, across all conditions only about 10% of customers did not purchase any items. Therefore, we see little evidence to suggest that bundling may be harmful in markets where some people comparison shop.

This research was motivated by a desire to study multi-product pricing behaviour in a competitive context. Controlled laboratory experiments enable one to identify treatment effects and empirical regularities such as fundamental biases in human decision makers. It bears mention that a concern is often raised by those first evaluating controlled laboratory experiments in which undergraduates serve as a proxy for real decision makers. This critique is addressed very well by a recent paper in Science (Falk and Heckman 2009) and we refer the skeptical reader to it. Here we simply note that, theoretical models such as the one in this paper, are silent on who or what the decision maker is and only posit that it is incentivized to maximize the given objective function. While one may think that experience will impact behavior, unless that experience interacts with the treatment effect the claim does not impact the comparative static results of interest rendering it pointless. However, if the experience of the decision makers is important, then one cannot make comparisons between interactions X and Y whether these are in two different industries, the same industries at different points in time, or the lab and the “real world”. One advantage that the lab offers over the field is the ability to directly manipulate the pool of decision makers ceteris paribus. That is one can use controlled laboratory experiments to test the degree to which experience impacts behavior. As described in Falk and Heckman (2009) when people have directly compared undergraduates to real people the results are generally similar. Thus, the results of controlled laboratory experiments give guidance to practitioners as to what they can expect in certain market settings and what behaviour they need to guard against.

One critical step in debiasing decision makers is to warn them about the bias, so that they can perhaps counteract the effects (Fischhoff 1982). Firms spend billions of dollars annually on training of which a large component is debiasing interventions (Tokar et al. forthcoming). The current research provides a first step toward understanding human biases in setting bundle prices, but there is much scope for further work that will advance theory and also improve practice in the field. As with any empirical project, one must be cautious when extrapolating the findings to different domains. For example, behaviour in the experiments would likely differ for different parameter values. Our choice of setting $\alpha = 0.8$ was so that half of the customers who visited a particular seller were comparison shoppers. The intent with equal likelihood of an informed or uninformed buyer visiting a given seller was to identify potential biases in pricing. A smaller faction of comparison
shoppers should lead to lower competitive pressure, a hypothesis that could be tested with further experiments. We picked a value of -0.3 as a “moderate” degree of substitutability and 0.3 as a “moderate” degree of complementarity as opposed to weak or strong values as defined by Venkatesh and Kamakura (2003). The choice was somewhat arbitrary, but if a particular parameter value is of interest, perhaps due to its similarity to some “real world” market, one can and should run additional experiments with that parameter value. The joint distributions used to generate (negative and positive) correlation between buyer values for the two products may be displayed to decision makers in alternative presentation modes. The software in the experiment display used a frequency grid (see Sedlmeier and Gigerenzer 2001) which is recognized to be easy to understand for people confronted with covariation. This was optimal for our purposes as we did not want confusion as to the distribution of buyer values driving seller behavior, but in most “real world” markets sellers do not actually know the distribution of buyer values and thus sellers have to make inferences about it, something else that could be studied directly in the laboratory.

REFERENCES


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http://www.theregister.co.uk/2006/08/15/beer_diapers/, on August 10, 2011.
Figure 1. Dominated Price Strategies by Treatment

Undominated Price Strategies for B

Undominated Price Strategies for θ⁺

Undominated Price Strategies for θ⁻

Undominated Price Strategies for V⁺

Undominated Price Strategies for V⁻
Figure 2. Average Efficiency by Session in Additivity Treatments
Figure 3. Average Efficiency by Session in Correlation Treatments