This research investigates how customer values for products influence mixed bundling strategies in competitive markets. Sellers set single item and bundle prices for buyers who are either comparison shoppers or who visit a single seller. We characterize the equilibrium condition for an oligopolistic model of bundling. We examine two features of distributions of customer values: additivity and correlations. For specific parameters of the model we compute solutions undominated by monopoly prices. Two experiments investigate bundling strategies by human decision makers: Experiment 1 studies markets for products that are complements or substitutes, by manipulating the additivity of customer valuations. Experiment 2 studies markets for products in which customer valuations of products are positively or negatively correlated. Across all conditions subject sellers actively engage in mixed bundling and we observe a systematic bias as human decision makers overemphasize comparison shoppers rather than acting as monopolists to buyers who do not comparison shop.

1. Introduction

Firms commonly use price bundling as a strategic marketing tool. Be it consumer packaged goods (e.g., a shrink wrapped package of shampoo and conditioner), consumer durables (e.g., computers and printers), services (e.g., cable TV and internet), firms use bundling as a means to improve measures of business performance including profits and market share. We are beginning to understand optimal pricing strategies, issues related to effective deployment of those strategies, and the environment in which these strategies may be deployed (Guiltnan 1987, Simon and Dolan 1998, Estelami 1999, Noble and Gruca 1999). Stremersch and Tellis (2002) survey the marketing, law, and economics literatures and develop a framework to synthesize the field of bundling. They iterate the
importance of developing expertise in designing bundling strategies, and also point out that the guidelines posited in their paper are a first step toward enhancing managerial insights on the optimality of bundling. They make three observations pertinent to the current literature on their assessment of the literature: Firstly (p. 60) that the literature has focused primarily on profit maximization by a monopolist. Secondly (p. 71) that one of the most promising areas of further research appears to be the impact of competition on the impact of bundling. Thirdly (p. 71), the relative importance of conditions for optimality still remains an open question for future research. In particular, they highlight the distribution of customer conditional reservation prices as the likely predominant condition for optimality of bundling.

The current research investigates how customer value structure for products and bundles influence strategic pricing behavior in competitive markets. With advances in technology and a proliferation of customer segment information services and software, firms have an increasing quantity of more granular and more immediate data available to them. Data mining techniques are used to transform this data into information on customer preferences for products, and also relationships between product preferences (see McCarty and Hastak 2007 for examples). In order to optimally leverage this information it is necessary to understand how these preferences interact with the competitive pricing practices of multiple firms in a dynamic setting.

We present an analytical model of optimal mixed bundle pricing in an oligopoly and use this model to investigate actual pricing behavior. Consistent with previous research that studied pricing behavior simpler settings, the model is too complex to solve in the general case. However, for specific parameters of the model we are able to solve
for undominated sets that contain the optimal mixed strategy equilibrium. Other than the case in which we assume that customer values for goods are independent and additive, we consider cases in which we relax each of these two assumptions in turn.

First we will investigate seller’s competitive pricing behavior when bundling products that are complements (customer values for the bundle are greater than the sum of the values for the individual products) or substitutes (customer values for the bundle are less than the sum of the valuations for the individual products). For example a computer and a printer are complements since customers have added utility for a printer when they have computer and vice versa. That is, the value of the bundle is greater than the sum of the values of the individual products. On the other hand a bottle of Pepsi and a bottle of Coke are substitutes. Since a customer who has a Coke has relatively little use for a Pepsi the value of bundle is less than the sum of the values of the individual products.

Second we will investigate seller’s competitive pricing behavior when bundling products which have positively or negatively correlated customer values. An example of negatively correlated products is a ticket to the ballet and a ticket to a wrestling match. A customer who has a high value for one of these tickets may be less likely to have a high value for the other. Two books on a related topic would likely have values that are positively correlated. Someone is likely to have high values for each or low values for each depending on the person’s level of interest in the topic. Notice that the additivity between values for two goods and the correlation of values for two goods are distinct concepts. Consider again the example of two books on the same topic that have positively correlated values. If the two books cover largely the same content then the
books are likely to be substitutes; however, if the books present related but distinct information then the two books are likely to be complements.

In the next section we review previous literature on bundling, and list unanswered questions that are addressed by the current research. Section 3 lays out the theoretical framework and presents the model of pricing behavior. Section 4 describes the experiment, Section 5 the results, and Section 6 contains concluding comments.

2. Previous Research on Bundling

Much previous research has analyzed bundling in a monopoly. Customers who have a high valuation for a favored product will buy a bundle although they may not pay the standalone price for the other unfavored product (Stigler 1968). Mixed bundling (offering both the separate products as well as the bundle) can be an effective tool for price discrimination even when the consumer’s willingness to pay for each good is not dependent upon his consumption or value of the other good and is independent across goods (Adams and Yellen 1976). The general result is that customers with a high degree of asymmetry in product valuations will buy an individual product that they favor, while customers with less extreme product valuations will buy the bundle. 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.

How to determine optimal bundle prices is the issue of prescriptive interest to firms. Hanson and Martin (1990) show how to compute optimal bundle prices using a mixed integer linear program. Mulhern and Leone (1991) develop a theoretical framework for retail pricing and promotion strategies based on implicit bundling of
related products. 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 price bundling. Venkatesh and Mahajan (1997) examine strategies for marketing products using their branded components. 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 determine 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.

Bakos and Brynjolfsson (1999) analyze the bundling of a large number of information goods. They use statistical techniques to derive results on optimal bundling strategies for products that are complements or substitutes, as well as products that may have correlated valuations. A feature that drives their results is that it is easier for a seller to predict how a customer may value a bundle of products than how they may value a single product. Hitt and Chen (2005) also study strategies for pricing a large number of information goods. They find that customized bundling that allows the customer to choose up to some quantity of products that are a subset of the larger pool of products outperforms pure components or pure bundles when goods have a positive marginal cost or when customers have heterogeneous preferences over goods. They also explore how the customized bundle solution is influenced by the correlations of values across goods as well as the complementarity and substitutability of goods. Nettesine, Savin, and Xiao (2006) present a stochastic dynamic program that analyzes the problem of dynamically
selecting complementary products, as well as the problem of pricing products to maximize profits.

There are a few studies that have studied bundling in competitive markets. McAfee, McMillan, and Whinston (1989) extend their monopoly results to a duopoly. 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. Bakos and Brynjolfsson (2000) extend their previous research to different competitive environments.

Table 1 summarizes the focus of previous research on bundling as a form of price discrimination and demonstrates how our work is distinct. In order to push the frontier of knowledge toward a set of conditions under which many markets operate, our research investigates seller’s price setting behavior when competing in oligopolies with informed/uninformed buyers à la Varian (1980). We compute the set of strategies undominated by monopoly pricing for the cases where customer values are additive, subadditive, superadditive, negatively correlated, and positively correlated. We then test behavior in two experiments: Experiment 1 features products with customer values that are subadditive, additive, or superadditive. Experiment 2 features products with customer values that are positively correlated, uncorrelated, or negatively correlated. To our knowledge our research is the first experimental test of bundling as a form of price discrimination.

Table 1: Summary of Previous Research.
3. Theoretical Model

There are three main arguments as to why firms would bundle, relying on exploitation of market power. The first is as an entry-deterrent strategy.\(^1\) In the second, a firm leverages market power in one market to capture a greater share of a more competitive market.\(^2\) The third considers bundling as a form of price discrimination. In this framework, sellers can charge relatively high prices to buyers with a high value for one product but a low value for the other, while retaining sells to buyers with more moderate values by offering a discount on the bundle.

Adams and Yellen (1976) lay out the general framework of the price discrimination model in which a monopolist sells two goods, A and B with marginal

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\(^1\) See Nalebuff (2004).

\(^2\) See Caliskan et al. (2007) for a discussion of this literature as well as an experimental test of such models.
costs $c_A$ and $c_B$, respectively. This monopolist can engage in pure bundling, meaning that the goods are only sold jointly, or mixed bundling, meaning that the goods are sold both jointly and separately.\textsuperscript{3} Buyers are assumed to have values for the goods given by $v_A$ and $v_B$, with the value of the bundle given by $v_{AB} = v_A + v_B$. Adams and Yellen (1976) show that bundling can be a profitable strategy even in the absence of complementarities in production or consumption.

The model we consider adopts this basic two-product framework and draws upon two other developments in the literature. Venkatesh and Kamakura (2003) extend the basic monopoly model by allowing values to be sub- or super-additive. Specifically, they consider a model in which $v_{AB} = (1+\theta) \times (v_A + v_B)$. When $\theta > 0$ the two goods are compliments and when $\theta < 0$ the two goods are substitutes. McAfee, McMillan, and Whinston (1989) revisit the model of Adams and Yellen (1976) allowing for values to be jointly distributed, $f(v_A, v_B)$. They find general conditions under which bundling is optimal and in which it can persist in a duopoly setting.

In our model $n$ identical sellers can produce goods A and B at marginal cost $c_A$ and $c_B$, respectively. Buyers demand at most one unit of each good with values distributed $f(v_A, v_B)$. Sellers can set prices $P_A$, $P_B$, and $P_{AB}$ for the single items A and B and the bundle AB. In this market sellers cannot monitor a buyer’s purchases meaning that a seller cannot charge more for the bundle than for the individual items, ie. $P_{AB} \leq P_A + P_B$.\textsuperscript{4} With the equality in this condition, a seller is engaging in pure component pricing.

\textsuperscript{3} The seller also has the ability to only sell the items separately, which is referred to as pure components.

\textsuperscript{4} See McAfee, et al. (1989) for a discussion of monitoring.
Following McAfee, et al. (1989) we assume that firms engage in simultaneous price setting. However, we further enhance the model by introducing 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 fully informed of all competitor prices while the remaining customers visit a single seller. This captures the notion that some potential customers comparison shop, pay attention to advertisements, etc., whereas others do not perhaps due to a preference for a certain retailer, an inability to travel, etc. Each of the $n$ firms acts as a monopolist to the $\alpha / n$ potential customers who only visit that seller, but the seller is unable to determine which customers comparison shop and which do not.\(^5\)

The problem faced by an uninformed potential customer with values $v_A$, $v_B$, $v_{AB}$ who observes prices of $P_A^i$, $P_B^i$, and $P_{AB}^i$ from seller $i$ is straightforward. The customer will purchase the bundle AB if $v_{AB} - P_{AB}^i > \max(0, v_A - P_A^i, v_B - P_B^i)$. Similar conditions hold for purchasing items 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.\(^6\) As argued by Venkatesh and Kamakura (2003) there is no closed form solution for this monopoly problem.

The problem faced by an informed customer 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 $v_{AB} - P_{AB}^i > \max(0, v_A - P_A^i, v_B - P_B^i, v_A - P_A^j, v_B - P_B^j, v_{AB} - P_{AB}^j)$ $\forall j \neq i$. The informed customer will purchase only item A from seller $i$ if $v_A - P_A^i >$

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\(^5\) See Deck and Wilson (2006) for theory and experiments regarding the ability to track customers in a single good market.

\(^6\) If $f(\cdot,\cdot)$ is continuous, such a tie occurs on a set of measure 0.
max \((0, v_{AB} - P^i_{AB}, v_B - P^i_B, v_A - P^i_A, v_B - P^j_B, v_{AB} - P^j_{AB})\) \(\forall j \neq i\) with a similar condition holding for purchasing item 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 the best decision from the \(3n+1\) choices and cannot create a bundle by purchasing components from different sellers.\(^7\)

Let \(\Pi^m\) denote the expected profits that monopolist would earn from setting the monopoly prices, and let each of the other \(n-1\) sellers set prices according to the joint distribution function \(g(P_A, P_B, P_{AB})\) in the oligopoly of size \(n\). The following equality characterizes the equilibrium condition:

\[
\int \int \int g(P_A, P_B, P_{AB}) \times E(\Pi|P^i_A, P^i_B, P^i_{AB}) = \alpha \Pi^m/n.
\]

**Proof:** In Appendix

Unfortunately, this model is not computationally tractable.\(^8\) Venkatesh and Kamakura (2003) show that for general \(\theta\), a closed form solution does not exist in the relatively simple monopoly problem, much less the oligopoly model we present here.

We do note that if \(\alpha=0\) then there is no competition and the equilibrium is for \(P^i_A = P^m_A\), \(P^i_B = P^m_B\) and \(P^i_{AB} = P^m_{AB}\) \(\forall i\). Of course, the monopoly prices are a function of \(f(v_A, v_B)\) and \(\theta\). On the other hand, if \(\alpha = 1\) and all customers comparison shop the equilibrium is \(P^i_A = c_A, P^i_B = c_B\) and \(P^i_{AB} = c_A + c_B \forall i\).

Theoretical complexity has not stopped non-monopoly sellers from engaging in bundling. In the naturally occurring market place, there are numerous examples of

\(^7\) Buyer behavior must be individually rational so the buyer has the option to buy nothing.

\(^8\) The two goods model discussed in this literature is itself a simplification of the more general \(k\) goods bundling problem. To our knowledge, this generalization has not been explored.
oligopolists selling bundled goods. The goal of this paper is to understand how the value structure affects market outcomes. Therefore we rely upon a series of controlled laboratory experiments in the absence of clear theoretical predictions. As described by Smith (1994) laboratory experiments provide a means for establishing empirical regularities and comparing environments. That is, through experiments we can identify how market outcomes change as a function of changes to the value structure.

Without directly solving for \( g(P_A, P_B, P_{AB}) \) we can identify price triples that are not in the support of the symmetric mixed strategy equilibrium. Note that the observation of such prices would indicate behavior that is inconsistent with the model. Any firm could operate as a monopolist to customers who only visit it and earn an expected profit of \( \alpha \Pi^m / n \). The profit of a price triple in the support of the mixed strategy equilibrium must generate a profit that exceeds \( (\alpha \Pi^m / n) / (1-\alpha + \alpha/n) \) from uninformed buyers where the denominator is the probability a firm is visited either by an informed or an uninformed shopper. Otherwise, the firm would prefer to receive the security profit.

While the theoretical model does not yield an equilibrium prediction, we use the model to gain some insight by restricting our analysis to specific parameter values.\(^9\) We then design experiments to test for seller behavior, assuming these specific parameter values: the number of firms \( n = 4 \), the proportion of comparison shoppers \( \alpha = 0.8 \), the marginal costs of goods A and B were \( c_A = c_B = 0 \). While it is difficult to determine the number of firms necessary for workable competition in antitrust settings, it has been suggested that 4 firms may be sufficient for good performance (see Holt 1995, p. 407). With \( \alpha = 0.8 \), 20% of customers comparison shop and 20% visit each of the 4 sellers.

\(^9\) We pick these parameter values because they lead to separation of equilibrium prices under monopoly conditions.
individually. Conditioned on a particular seller being visited, there is a 50% chance that the seller is in direct competition for a comparison shopper.

In our baseline condition, the goods are neither complements nor substitutes ($\theta = 0$) and buyer values are independently distributed. Our experiments vary the degree of complementarity (Experiment 1) and the correlation of buyer values (Experiment 2). The focus of this paper is on the main effect of each factor and thus we consider the degree of complementarity and correlation separately. In Experiment 1, $\theta^+$ and $\theta^-$ denote the treatments in which $\theta = 0.3$ (complements) and $-0.3$ (substitutes), respectively. In all cases, the buyer demands at most one unit of each good. For $\theta^+$, $\theta^-$ and the baseline $v_A \sim \text{discrete } U[0,100]$ and $v_B \sim \text{discrete } U[0,100]$. In Experiment 2, $V^+$ and $V^-$ denote the treatments with positively and negatively correlated values, respectively. For $V^+$, $f(v_A,v_B) = \frac{1}{7651} \begin{cases} 1 & \text{if } |v_A - v_B| \leq 50 \\ 0 & \text{else} \end{cases}$ for $v_A, v_B$ integers $\in [0,100]$. For $V^-$, $f(v_A,v_B) = \frac{1}{7651} \begin{cases} 1 & \text{if } 50 \leq |v_A - v_B| \leq 150 \\ 0 & \text{else} \end{cases}$ for $v_A, v_B$ integers $\in [0,100]$. In $V^+$ and $V^-$ the goods are neither complements nor substitutes, $\theta = 0$. The correlation of $v_A$ and $v_B$ is $\rho = +0.5$ in $V^+$, $\rho = -0.5$ in $V^-$, and is $\rho = 0$ in the other three treatments. Table 2 gives the monopoly profit for each treatment in both experiments and Figure 1 shows the strategies that are not dominated by a firm setting the monopoly prices for each of the conditions in Experiments 1 and 2.\textsuperscript{10} That is, the symmetric Nash equilibrium prediction is that all price triples will be contained in the sets identified in Figure 1.

\textsuperscript{10} As discussed above, a strategy cannot be part of the equilibrium mixing distribution if it generates a profit less than $(\alpha \Pi^m/n) / (1-\alpha+\alpha/n) = .5\Pi^m$. 

12
Table 2. Optimal Prices and Profits for a Monopolist by Treatment

<table>
<thead>
<tr>
<th>Condition</th>
<th>ρ</th>
<th>θ</th>
<th>$P_A^m$</th>
<th>$P_B^m$</th>
<th>$P_{AB}^m$</th>
<th>$\Pi^m$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Substitutes $\theta^-$</td>
<td>0</td>
<td>-0.3</td>
<td>61</td>
<td>70</td>
<td>42.44</td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>0</td>
<td>0</td>
<td>67</td>
<td>87</td>
<td>55.04</td>
<td></td>
</tr>
<tr>
<td>Complements $\theta^+$</td>
<td>0</td>
<td>0.3</td>
<td>83</td>
<td>109</td>
<td>70.67</td>
<td></td>
</tr>
<tr>
<td>Negative Correlations</td>
<td>-0.5</td>
<td>0</td>
<td>36</td>
<td>62</td>
<td>59.95</td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>0</td>
<td>0</td>
<td>67</td>
<td>87</td>
<td>55.04</td>
<td></td>
</tr>
<tr>
<td>Positive Correlations $V^+$</td>
<td>0</td>
<td>52</td>
<td>88</td>
<td>52.02</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

< Insert Figure 1 here: Undominated Strategies

The choices for $\theta$ and $f(v_A, v_B)$ as evidenced by Table 2 and Figure 1 provide separation in the monopoly predictions and the set of prices that are not dominated by concentrating on uniformed buyers.\(^\text{11}\)

4. Experimental Design

The 80 unique participants were drawn from undergraduate business school classes at a state university in the US.\(^\text{12}\) Once subjects entered the laboratory, they were seated at computers surrounded by privacy dividers. This ensured that subjects could not observe other sellers’ screens or make eye contact with other participants. Each laboratory market consisted of four anonymous sellers. Subjects first read treatment specific written directions. After reading the directions, subjects completed a handout to verify that they

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\(^\text{11}\) Additionally, the distributions were selected because of the ease with which they can be explained to subjects.

\(^\text{12}\) The laboratory where these experiments were conducted, maintains a database of over 1000 eligible volunteer subjects. This database primarily consists of students who have taken business school classes, but it is open to all students on campus and does include a few students who are not connected to the business school.
understood the experiment. The handout was reviewed by the experimenters and the subjects had ample opportunity to ask questions. Once all subjects were ready, they set their initial prices and the experiment began.

In total, 20 sessions were conducted, four replications in each of the five treatments. Multiple sessions were conducted concurrently, so subjects did not know exactly which three other participants were in the market but they knew that the same three competitors remained in the market for the entire experiment. The practice of running multiple sessions concurrently with subjects being randomly assigned to markets also controls for idiosyncrasies during a particular time in the laboratory.

The sessions lasted for approximately 90 minutes, after which the subjects were paid their earnings in private and dismissed from the experiment. A subject’s payment was based upon the profit they earned in the experiment. All values, costs, and prices were in experimental dollars which were converted into $US at the rate of $Exp 400 = $US 1. The average of the performance based earnings across all sessions was $18.16. Each subject also received an additional $7.50 show-up payment for participating.

Since buyers in this market demand a single unit of each good, they have no incentive not to truthfully reveal their willingness to pay. As such, buyers were implemented with automated robots, a standard practice in experimental posted offer markets when the effect of demand withholding is not central to the research question (see Davis and Holt 1993, p. 177 for details). As previously described in section 3, 80% of buyers visited only one of these four sellers (equally distributed). The remaining 20% of buyers were comparison shoppers. Each experiment lasted for 750 periods. In each

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13 A copy of the baseline directions is included in Appendix A and a copy of the handout seen by all subjects is included in Appendix B. Copies of the other directions are available from the authors upon request.
period one robot buyer entered the market once, observed the relevant prices, made a purchase decision based upon the randomly determined values, and exited the market. A period lasted 3 seconds, during which time the four human sellers could observe the three prices posted by each of their rivals as well as which sellers were visited that period and what if any profit was realized by a seller. Subject sellers could update their own posted prices at any time during the experiment, 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 were common information among the sellers.

This decision environment is extremely complex. To aid the subject sellers, an onscreen tool would plot $R_{A}^{i}$, $R_{B}^{i}$, and $R_{AB}^{i}$ for any set of prices the subject provided. This tool also calculated the expected profit to a monopolist from the given set of prices. Figure 2 shows an example of this portion of the subject screen for the baseline condition. The bottom right shows the entire space of potential buyers. A subject could click on that chart and the chart on the bottom left would zoom to that region, providing specific values of potential buyers. The tool is color coded so that $R_{A}^{i}$ is yellow, $R_{B}^{i}$ is blue, and $R_{AB}^{i}$ is green as it is a combination of yellow and blue. The white region denotes buyers who would not purchase anything at the given prices. For treatments $V^{+}$ and $V^{-}$ in Experiment 2, the regions from which buyer values could not be drawn were shaded in black.
5. Results

The results of each experiment examine three issues: The first is the frequency with which sellers engaged in mixed bundling across treatments (levels of additivity and levels of correlation). The second is the treatment effect on market outcomes such as the prices and the quantities of goods that trade. Finally, the results examine the allocation of trade surplus between buyers and sellers.

5.1 Experiment 1 – Manipulating $\theta$

Bundling Strategies

First we ask if subjects choose to engage in mixed bundling or prefer to focus on pure bundling or pure components in these environments. The experimental design allows subjects to engage in pure bundling by setting the bundle price at or below the price of the individual items or in pure components by setting the bundle price equal to the sum of the individual items. We define a price ratio as $P_{AB}/(P_A+P_B)$ and thus pure components has a price ratio of 1 while pure bundling has a price ratio less than or 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 3 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.

Table 3. Frequency of Pricing Strategy in Experiment 1

<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>θ⁺</td>
<td>84%</td>
<td>12% (21%)</td>
<td>4% (5%)</td>
</tr>
<tr>
<td>Baseline</td>
<td>83%</td>
<td>14% (17%)</td>
<td>3% (6%)</td>
</tr>
<tr>
<td>θ⁻</td>
<td>80%</td>
<td>14% (18%)</td>
<td>6% (10%)</td>
</tr>
</tbody>
</table>

Treatment effect on price setting behavior

We now examine the actual prices posted by sellers. To control for learning effects, estimation is restricted to the last 500 periods of the experiment. We present two sets of results for both single item prices and bundle prices: one based upon the average price in a market which is the typical price observed by a buyer that does not comparison shop and one based upon the minimum price in the market which is 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 the repeated measures within a session, we employ a linear mixed effects model allows for both a treatment fixed effect and a session random effect. The estimation results are presented in Table 4.

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14 Statistically, there is no difference between the price of set for good A and B in any treatment of either experiment. Therefore, we combine the observations of good A and good B prices.
Table 4. Linear Mixed Effect Estimation for Mean / Minimum Prices in Experiment 1

<table>
<thead>
<tr>
<th></th>
<th>Mean Prices</th>
<th></th>
<th>Minimum Prices</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Single Item</td>
<td>Bundle</td>
<td>Single Item</td>
<td>Bundle</td>
</tr>
<tr>
<td>Constant</td>
<td>40.5*</td>
<td>55.7*</td>
<td>27.5*</td>
<td>37.2*</td>
</tr>
<tr>
<td></td>
<td>(12.27)</td>
<td>(8.87)</td>
<td>(10.58)</td>
<td>(6.49)</td>
</tr>
<tr>
<td>PosT</td>
<td>-1.6</td>
<td>0.4</td>
<td>-1.06</td>
<td>-0.6</td>
</tr>
<tr>
<td></td>
<td>(-0.33)</td>
<td>(0.04)</td>
<td>(-0.29)</td>
<td>(-0.08)</td>
</tr>
<tr>
<td>NegT</td>
<td>-2.0</td>
<td>-6.98</td>
<td>-2.31</td>
<td>-4.2</td>
</tr>
<tr>
<td></td>
<td>(-0.42)</td>
<td>(-0.79)</td>
<td>(-0.63)</td>
<td>(-0.52)</td>
</tr>
</tbody>
</table>

Each of the four models is estimated separately. PosT and NegT are dummy variables that take on a value of 1 if the observation is from a session in which $\theta$ is positive or negative respectively. * denotes significant difference from 0 at the 5% level in a two sided t-test and t-statistics are presented in parentheses.

The coefficients in PosT and NegT give the treatment effects. For example, the average single item price in the baseline is 40.5 while the average single item price in $\theta^+$ is $40.5 - 1.6 = 38.9$, which is not statistically different from the mean of the baseline case. Based upon the results presented in Table 4, changes in $\theta$ do not significantly affect the typical market price of either single items or bundled items.

That there was no significant variation of average single item and bundle prices across treatments does not imply that subject behavior did not change across treatments. A subject seller is making a joint decision for single item and bundle prices. An alternative way to think of this is that sellers are setting single item prices and determining what discount to place on the bundle relative to the sum of the single item prices. Across treatments in Experiment 1, sellers are changing bundle prices at different rates as they adjust single item prices. Table 5 gives the linear mixed effects estimation for the change in the bundle price resulting from a change in the average single item price a seller is charging. Here the unit of measurement is the individual during a period in a given session and in addition to a session random effect each subject is assumed to have a random effect as well.
Table 5. Linear Mixed Effect Estimation for Change in Bundle Price for a Change in Single Item Price in Experiment 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>SIPrice</th>
<th>SIPxPosT</th>
<th>SIPxNegT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>0.28*</td>
<td>.75*</td>
<td>.47*</td>
</tr>
<tr>
<td>t-statistic</td>
<td>(18.09)</td>
<td>(25.70)</td>
<td>(16.79)</td>
</tr>
</tbody>
</table>

Note: The dependent variable is the difference between the observed bundle price and the average bundle price from that treatment. PosT and NegT are dummy variables that take on a value of 1 if the observation is from a session in which θ is positive or negative respectively. SIPrice is the deviation of the average single item price set by the seller and the average single item price in the treatment from which the observation originates. No constant term is included as everything is measured as a deviation from the mean. * denotes significant difference from 0 at the 5% level in a two sided t-test.

The results in Table 5 show that for every dollar increase in the average single item price of a seller, the seller raises her bundle price by 0.28 dollars in the baseline case. In the θ⁺ treatment the same increase in the average single item price results in a 0.28 + 0.75 = 1.03 increase in the bundle price. In the θ⁻ treatment the same increase in average single item price results in a 0.28 + 0.47 = 0.75 increase in the bundle price. For both treatments in Experiment 1, sellers adjust their bundle prices more dramatically as they adjust their single item price; the effect is more pronounced in θ⁺ than in θ⁻.

Consistency of price setting behavior with the model

There was great variation in single item and bundle prices, which one would expect if subjects were playing a mixing strategy. However, subjects regularly set prices that are dominated by the monopoly strategy.¹⁵ Furthermore we define a price triple as being too low if it is not in the undominated set, 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 θ⁺ and θ⁻ the percentages of price triples outside the indicated

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¹⁵ Subjects were not informed of the monopoly prices.
area in Figure 1 over the last 500 periods were 42% and 57% respectively. Of these, the percentages that were too low were 89% and 80% respectively. This behavior is not consistent with the symmetric mixed strategy Nash equilibrium derived in the Appendix. 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 the superadditive and subadditive conditions relative to the baseline condition.

We also examined the impact of competitive pricing behavior on profitability. For each subject we computed the percentage of periods in which they had the lowest price in their market for either an individual good or the bundle to serve as a metric for competitiveness. The correlation of this competitive metric with profit was positive for the baseline condition (0.21), the superadditive condition (0.28), and the subadditive condition (0.57). We do not report the results of statistical tests such as a Pearson’s correlation test because the percentage of time that subjects in the same session charged the lowest price necessarily sums to one, thus violating the assumption of independence necessary for testing (though not for point estimation). We do however note that the positive correlations have both a descriptive implication and prescriptive implications. The general tendency across the board is to set prices lower than the optimal set, so that those firms that set the most competitive prices capture most of the informed buyers and thus make somewhat higher profits. However if firms did not attempt to keep up with

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16 We do not compare these percentages across treatments as the number of strategies in the space shown in Figure 1 varies widely by treatment.
17 Note that we can identify behavior that is inconsistent with the model even though we cannot derive explicit predictions.
18 This pattern is similar to what was observed in Deck and Wilson (2006); however, there was less space between the minimum price in the mixing distribution and the minimum possible price a seller could charge in that study.
19 We also computed similar correlations of profit with the percentage of periods that a subject had the lowest price for an individual good and the percentage of periods in which they had the lowest price in the market for the bundle, and found a similar pattern for these correlations.
competitors and instead focused on selling to their uninformed buyers they should be better off. That is, being somewhat competitive (i.e., near but not at the lowest price) is not advisable in this stylized setting in which buyers are either informed or uninformed.

*Purchase outcomes and market efficiency*

The low prices observed in the market benefit the consumers, enabling them to increase their purchases relative to the monopoly situation. Table 6 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 the results presented in Table 6 is the result that bundle purchasers as a percentage of customers increase with theta. Also evident from the table is that the increase in bundle sales is coming at the expense of single item sales, not from a decrease in the percentage of consumers who do not purchase which remains fairly constant.

<table>
<thead>
<tr>
<th>Table 6. Distribution of Purchase Outcomes</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Buy Nothing</strong></td>
</tr>
<tr>
<td><strong>Baseline</strong></td>
</tr>
<tr>
<td>12% : 33%</td>
</tr>
<tr>
<td>$\theta^+$</td>
</tr>
<tr>
<td>$\theta^-$</td>
</tr>
</tbody>
</table>

We conclude our discussion of Experiment 1 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 for a
discussion of efficiency in standard posted offer markets). Figure 3 plots the average efficiency of each session. Visually, there is no difference across treatments, a conclusion that is supported by the linear mixed effects estimation.²⁰

Figure 3. Efficiency by Session in Experiment 1

![Bar chart showing efficiency by session.]

Market efficiency measures how the market as a whole performs, but not how buyers and sellers fare relative to each other. The left hand panel of Figure 4 plots the average buyer surplus by session. Clearly, buyer surplus increases with theta.²¹ As theta increases there is more potential surplus, so buyer surplus increasing does not necessarily mean that seller surplus is decreasing. The right hand panel of Figure 4 plots seller surplus, which is nominally though not significantly increasing in theta. Ultimately this implies that in competitive environments, buyers retain most of the benefits of increasing value additivity, a conclusion supported by the linear mixed effects results presented in Table 7. Based upon those results, sellers receive $0.30 of every dollar of potential surplus in the baseline but only $0.21 cents of every dollar of potential surplus in $\theta^+$.

²⁰ Based upon the estimation, average efficiency was 85% in the baseline and the coefficients for $\theta^+$ and $\theta^-$ were 0.00 and 0.02 respectively with p-values of 0.789 and 0.324 respectively.

²¹ Pair wise comparisons of the treatments based upon the Mann Whitney test supports this conclusion.
Figure 4. Buyer (Left) and Seller (Right) Surplus by Session in Experiment 1

Table 7. Linear Mixed Effects Estimation for Seller’s Share of Potential Surplus

<table>
<thead>
<tr>
<th>Variable</th>
<th>PotSur</th>
<th>PotSus x PosT</th>
<th>PotSur x NegT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>0.30*</td>
<td>-0.09*</td>
<td>0.09*</td>
</tr>
<tr>
<td>t-statistic</td>
<td>(28.68)</td>
<td>(-6.96)</td>
<td>(4.72)</td>
</tr>
</tbody>
</table>

The dependent variable is the profit made by the seller. PosT and NegT are dummy variables that take on a value of 1 if the observation is from a session in which $\theta$ is positive or negative respectively. PotSur is the potential surplus available in the market given the values of the buyer. * denotes significant difference from 0 at the 5% level in a two sided t-test.

5.2 Experiment 2 – Manipulating $\rho$

Bundling Strategies

The results for Experiment 2 are presented in the same order and fashion as the results for Experiment 1; therefore, some details are omitted for brevity. The baseline is the same as in Experiment 1. Table 8 presents the frequency with which sellers engaged in the various pricing strategies in Experiment 2. As evidenced in the table, sellers are again overwhelmingly utilizing mixed bundling. The frequency with which sellers engage in pure component pricing or pure bundling is comparatively small.
Table 8. Frequency of Pricing Strategy in Experiment 2

<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>

*Treatment effect on price setting behavior*

Table 9 provides evidence of the treatment effect on observed single item and bundle prices based upon a linear mixed effects model where each session has a random effect on behavior. As before, we restrict our attention to the last 500 periods and evaluate the typical price observed by both informed and uninformed buyers.

Table 9. Linear Mixed Effect Estimation for Average / Minimum Prices in Experiment 2

<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>
</tbody>
</table>

Each of the four models is estimated separately. PosT and NegT are dummy variables that take on a value of 1 if the observation is from a session in which \( \theta \) is positive or negative respectively. * denotes significant difference at the 5% level in a two sided t-test. Corresponding t-statistics are presented in parentheses.

In the V⁺ condition, individual items are significantly lower than those in the baseline. Bundle prices, though nominally lower in V⁺, are not significantly different. However, we find no significant differences between the baseline and the V⁻ treatment. Again, there was considerable variability in prices, as would be consistent with subjects playing a mixed strategy.
As in Experiment 1, sellers are changing bundle prices at different rates as they adjust single item prices. Table 10 gives the linear mixed effects estimation for the change in the bundle price resulting from a change in the average single item price a seller is charging. Based upon the results presented in Table 10, an increase in the average single item price charged by a seller results in a bundle price that increases by $0.28 + 0.56 = $0.84$ in $V^+$ and an increase of $0.28 + 0.75 = $1.03$ in $V^-$. In both treatments of Experiment 2, sellers adjust their bundle prices more dramatically as they adjust their single item price; the effect is more pronounced in $V^-$ than in $V^+$.

Table 10. Linear Mixed Effect Estimation for Change in Bundle Price for a Change in Single Item Price in Experiment 2

<table>
<thead>
<tr>
<th>Variable</th>
<th>SIPrice</th>
<th>SIPxPosT</th>
<th>SIPxNegT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>0.28*</td>
<td>.56*</td>
<td>.75*</td>
</tr>
<tr>
<td>t-statistic</td>
<td>(21.31)</td>
<td>(21.08)</td>
<td>(19.01)</td>
</tr>
</tbody>
</table>

The dependent variable is the difference between the observed bundle price and the average bundle price from that treatment. PosT and NegT are dummy variables that take on a value of 1 if the observation is from a session in which $\rho$ is positive or negative respectively. SIPrice is the deviation of the average single item price set by the seller and the average single item price in the treatment from which the observation originates. No constant term is included as everything is measured as a deviation from the mean. * denotes significant difference from 0 at the 5% level in a two sided t-test.

Consistency of price setting behavior with the model

As in Experiment 1, subjects in Experiment 2 are too competitive. In $V^+$, 53% of the prices set in the last 500 periods were outside the region shown in Figure 1. For $V^-$ this percentage was 67%. In the $V^+$ and $V^-$ conditions respectively, 63% and 58% of these price triples were too low. This shows that subject behavior is not consistent with the symmetric mixed strategy Nash equilibrium derived in the Appendix.

Again, we examined the correlations of the percentage of time a seller set the lowest price for a single item or the bundle with profit. Contrary to Experiment 1, we
found that correlations were negative for the $V^+$ condition (-0.66) and the $V^-$ condition (-0.42). Therefore subjects who charge the lowest prices tended to do worst. The explanation for this reversal is that in these treatments, there is less of a tendency to set prices below the optimal set, as compared to the superadditive and subadditive conditions (63% and 58% as compared to 89% and 80%). That is, rather than being just above the lowest price seller as in the treatments that vary $\theta$, here the other sellers tend to charge prices substantially above their low price competitors. Sellers that set the most competitive prices clearly forego potential profits from selling to their uninformed buyers, which the other sellers are more likely to exploit in the correlation treatments.

Purchase outcomes and market efficiency

Again, the relatively low prices observed in the market benefit the consumers, enabling them to increase their purchases relative to the monopoly situation. Table 11 compares the observed percentage of each buyer with the percentage that would be expected to buy those items under monopoly conditions. Fewer buyers make no purchase 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. Differences between the baseline and $V^+$ are not significant, but nominally it appears that positively correlated values leads single item purchasers to become bundle purchasers.

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22 Correlations of profit with the percentage of periods that a subject had the lowest price for an individual good and the percentage of periods in which they had the lowest price in the market for the bundle had a similar pattern.
Table 11. 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: Monopoly</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>13%:35%</td>
<td>10%:10%</td>
<td>77%:51%</td>
<td></td>
</tr>
<tr>
<td>4%:22%</td>
<td>29%:38%</td>
<td>67%:66%</td>
<td></td>
</tr>
</tbody>
</table>

Having established how prices and quantities change with the correlation of values, we conclude our discussion of Experiment 2 by examining the welfare implications of the treatment effects. Figure 5 plots the average efficiency of each session. Visually, there is no difference between the baseline and the V⁺ condition, however, the V⁻ condition is higher. This is supported through linear mixed effects estimation.23

Figure 5. Efficiency by Session in Experiment 2

![Figure 5](image.png)

Unlike changes in θ, changes in correlation do not generate additional surplus. Figure 6 plots average surplus for buyers (left) and sellers (right) by session. Based upon Mann Whitney tests, there are no differences between treatments in the amount of surplus.

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23 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.
buyers obtain nor is there a difference in the surplus obtained by sellers even though sellers appear to do relative worse with positively correlated values.\textsuperscript{24}

Figure 6. Buyer (Left) and Seller (Right) Surplus by Session in Experiment 2

Table 12 reports the mixed effects estimation for how an additional dollar of potential surplus is split between the buyers and sellers. For each dollar of potential surplus in $V^-$ sellers receive $.30 + .01 = $0.31$ which is statistically the same as the $0.30$ captured in the baseline. However, the sellers are less successful at capturing surplus in $V^+$ where they only receive $.30 - .07 = $0.23$ of every dollar of potential surplus.

Table 12. Linear Mixed Effects Estimation for Seller’s Share of Potential Surplus

<table>
<thead>
<tr>
<th>Variable</th>
<th>PotSur</th>
<th>PotSur x PosT</th>
<th>PotSur x NegT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>0.30*</td>
<td>-0.07*</td>
<td>0.01</td>
</tr>
<tr>
<td>t-statistic</td>
<td>(30.81)</td>
<td>(-5.41)</td>
<td>(0.76)</td>
</tr>
</tbody>
</table>

The dependent variable is the profit made by the seller. PosT and NegT are dummy variables that take on a value of 1 if the observation is from a session in which $\rho$ is positive or negative respectively. PotSur is the potential surplus available in the market given the values of the buyer. * denotes significant difference from 0 at the 5% level in a two sided t-test.

6. Discussion

Much of the research on bundling as a form of price discrimination has focused on monopoly markets, and the current research extends to the competitive environments

\textsuperscript{24} These two statements are not redundant as the level of efficiency is greater in $V^-$. 
in which most sellers use the practice as a strategic option. Previous research has shown that bundling can be optimal even when a potential buyer’s values for the two goods are unrelated and the bundle value is simply the sum of the value of the parts. The optimal single item price and bundle price for a monopolist change as the relationship between the two goods changes. We study the effects of changes in this relationship in two respects: additivity of the two individual values, and correlation between the two individual values. Given the availability of data sellers through technology, it is possible to identify where pairs of goods fall along these two dimensions. Our research looks at how these variables impact changes impact behavior in competitive markets with the purpose of helping identify the likely impacts of bundling and suggesting ways that sellers can engage in the practice more effectively.

Our experiments incorporate many features of naturally occurring markets. Retailers compete with other firms for comparison shoppers, although they also sell to a loyal customer base that will not comparison shop at these competing firms. The level of additivity and correlation can be explicitly controlled in the laboratory. Such experiments allow us to identify the direction and magnitude of biases that people may display, along with the dynamic consequences of these biases in a complex decision environment with many agents.

6.1 Limitations and Directions for Future Research

The model we develop in our attempt to move toward ecological realism is still simpler than the task faced by sellers in the naturally occurring marketplace. Due to computational intractability of the analytical model, we turn to controlled laboratory experiments to provide further insight into this phenomenon. We do however offer
similar caveats as do others who run such laboratory studies (see for example Amaldoss and Rapoport 2005): we test model implications rather than model assumptions, we recruit student subjects for small rewards in our experiments rather than brand managers, and individual subjects represent firms rather than the category teams that make such pricing decisions.

Several streams of research have studied customer response to bundling promotions (see for example Harris and Blair 2006, Foubert and Gijsbrechts 2007, Wathieu and Bertini 2007), and so we are developing an understanding of the psychology of the consumer in monopolistic settings. Future research may incorporate these insights on the consumer side to competitive settings.

6.2 Conclusions

We find that sellers overwhelmingly engage in bundling. However, subjects tend to overemphasize the degree of competition and push prices down too low in an attempt to gain market share. This is true across the all treatments although it is more prominent when product values are superadditive or subadditive, than when values are positively or negatively correlated. We do not see changes in average single item prices or average bundle prices when we manipulate the additivity of the bundle values, as might be expected. What does change along this dimension is the discount sellers are offering on the bundle. In general sellers adjust their bundle prices more with a change in single item prices in both the subadditive and superadditive treatments relative to the baseline in which values were additive. The tendency to push prices too low is inconsistent with the symmetric Nash equilibrium mixing distribution.
As may be expected, we do observe single item prices falling relative to the baseline and bundle prices holding constant when buyer values are positively correlated. However, we did not observe expected price movements for the negatively correlated treatment. It appears therefore that human judgment performs better in the case with positively correlated values. Even in the negatively correlated values condition there is less evidence of a systematic bias toward an overemphasis on competition than in the treatments involving subadditivity or superadditivity. These experimental findings may motivate research on potential judgment and decision biases that have these detrimental effects on the efficiency of pricing by human decision makers. These insights may then provide warnings to the decision makers and enable the design of automated systems and training programs that help improve pricing decisions in various contexts.

An advantage of the laboratory is that we can measure the welfare implications of the treatment effects. In all cases efficiency, a measure of the potential gains from trade that are realized was high although it was highest when values were negatively correlated. Across all conditions only about 10% of customers did not purchase any item. In the baseline buyers managed to keep approximately $0.30 on every dollar of potential surplus, that is, they pay 70% of their willingness to pay. While in general, sellers were more successful at capturing surplus as the degree of additivity decreased, the effects of competition are quite beneficial to consumers.

While we found differences between treatments in the degree and nature of an overemphasis on competition, the major insight from this research is that human decision makers are likely to engage in over-competitive pricing. Those who make pricing
decisions in environments that feature the factors incorporated in our studies may choose to consider these findings as inputs in order to improve their profits.
Appendix: Derivation of the symmetric equilibrium condition

In looking for a symmetric Nash equilibrium we note that no pure strategy equilibrium is possible as a probability of a tie would cause the seller to prefer a price just below the price identified in the strategy. By the same logic no symmetric equilibrium strategy that places a positive weight on any price is possible. As a first step, we need to determine the security profit that a firm could earn. A seller in this setting could opt to focus only on the potential customers who will visit and not comparison shop.

Let \( P_A^m, P_B^m, \) and \( P_{AB}^m \) denote the prices a monopolist would charge and let \( \Pi^m \) denote the expected profits that monopolist would earn from setting the monopoly prices. We introduce the notation \( R_A^i, R_B^i, \) and \( R_{AB}^i \) to denote the region of possible buyer values from which a buyer who only visited seller \( i \) would choose to purchase A, B, and the bundle AB from seller \( i \) given \( P_A^i, P_B^i, \) and \( P_{AB}^i \). Therefore \( \Pi^m = (P_A^m - c_A) \int \int_{R_A^i} f(v_A, v_B) + (P_B^m - c_B) \int \int_{R_B^i} f(v_A, v_B) + (P_{AB}^m - c_A - c_B) \int \int_{R_{AB}^i} f(v_A, v_B) \). The security profit for a competitive firm, that is the expected profit that a firm can guarantee its self, is thus \( \alpha \Pi^m/n \).

Alternatively, a firm could attempt to compete with its \( n-1 \) rivals to attract comparison shoppers. In this case the firm will earn a profit of \( P_A^i - c_A \) if the buyer is in region \( R_A^i \) which occurs with probability \( \int \int_{R_A^i} f(v_A, v_B) \) and either does not comparison shop (probability \( \alpha/n \)) or does comparison shop (probability \( 1-\alpha \)) and seller \( i \) is offering the best deal to the buyer. The probability that seller \( i \) is offering the best deal is the probability seller \( i \) is offering a better deal than some seller \( j \neq i \) raised to the \( n-1 \) power as each seller is selecting prices independently. Suppose that each of the other \( n-1 \) sellers
set prices according to the joint distribution function $g(P_A, P_B, P_{AB})$. The probability that $i$ is offering a better deal than $j$ given that the buyer is in $R^i_A$ is the probability that the buyer is also in $R^j_A$ and seller $i$ has the better deal which can be expressed as

$$\int \int f(v_A, v_B) \times \int \int g(P_A, P_B, P_{AB})$$

plus the probability that the buyer is in $R^j_B$ and seller $i$ has the better deal which can be expressed as

$$\int \int f(v_A, v_B) \times \int \int g(P_A, P_B, P_{AB})$$

plus the probability that the buyer is in $R^j_{AB}$ and seller $i$ has the better deal plus the probability that the buyer is unwilling to buy from seller $j$. Similar profit conditions hold for $R^i_B$ and $R^i_{AB}$. Therefore, the expected profit from prices $(P^i_A, P^i_B, P^i_{AB})$ would be as follows

$$E(\Pi | P^i_A, P^i_B, P^i_{AB}) = \left\{ \left(P^i_A - c_A\right) \times \int \int f(v_A, v_B) \times \{\alpha/n + (1-\alpha)\} \times \prod_{j=1 \text{ to } n, j \neq i} \left[ \int \int f(v_A, v_B) \right] \times \int \int g(P_A, P_B, P_{AB}) \right\} + \left\{ \left(P^i_B - c_B\right) \times \int \int f(v_A, v_B) \times \{\alpha/n + (1-\alpha)\} \times \prod_{j=1 \text{ to } n, j \neq i} \left[ \int \int f(v_A, v_B) \right] \times \int \int g(P_A, P_B, P_{AB}) \right\} + \left\{ (P^i_{AB} - c_A - c_B) \times \int \int f(v_A, v_B) \times \{\alpha/n + (1-\alpha)\} \times \prod_{j=1 \text{ to } n, j \neq i} \left[ \int \int f(v_A, v_B) \right] \times \int \int g(P_A, P_B, P_{AB}) \right\} + \left\{ (P^i_{AB} - c_A - c_B) \times \int \int f(v_A, v_B) \times \{\alpha/n + (1-\alpha)\} \times \prod_{j=1 \text{ to } n, j \neq i} \left[ \int \int f(v_A, v_B) \right] \times \int \int g(P_A, P_B, P_{AB}) \right\}$$
\[
\int \int f(v_A, v_B) \times \int \int g(P_A, P_B, P_{AB}) + \int \int f(v_A, v_B) \times \int \int g(P_A, P_B, P_{AB}) + \\
\int \int f(v_A, v_B) \quad \}
\]

The expected profit from using the distribution \( g(P_A, P_B, P_{AB}) \) would be

\[
\int \int g(P_A, P_B, P_{AB}) \times E(\Pi | P_A^i, P_B^i, P_{AB}^i). \quad \text{For } g(P_A, P_B, P_{AB}) \text{ to be a symmetric mixed strategy equilibrium, players must be indifferent over all pure strategies in the support of the mixing distribution and the mixing distribution, see Varian (1980). That is the mixing distribution is such that } \int \int g(P_A, P_B, P_{AB}) \times E(\Pi | P_A^i, P_B^i, P_{AB}^i) = \alpha \Pi^m / n.
\]
References


Figure 1: Undominated Strategies

Undominated Strategies Baseline Condition

Undominated Strategies Negative Theta

Undominated Strategies Positive Theta

Undominated Strategies Negatively Correlated Values

Undominated Strategies Positively Correlated Values
Appendix A. Subject Directions for Baseline Condition

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, and price for the bundle that consists of goods A + B. Notice that the directions and the computer interface are color-coded and make use of the fact that yellow and blue make green. You do not incur any cost to produce the goods you sell, and thus your profit equals the selling price if you make a sell. The other three sellers do not have any costs either.

**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 value for good A is drawn randomly from [0,1,2,...,99,100]. This means that the buyer’s value for good A is equally likely take any integer value from 0 to 100. The buyer’s value for good B is also drawn randomly from [0,1,2,...,99,100]. Notice that the values of good A and good B are independent, meaning that a buyer’s value of good A does not tell you anything about the buyer’s value for good B.

The buyer’s value of the bundle that consists of goods A + B equals (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 the bundle of goods A + B equals (30+70) = 100.*

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 bundle. 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 80% 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 has four options: buy good A only, buy good B only, buy the bundle A+B, or buy nothing. The buyer will select the option that is best for the buyer. Note that a buyer could create the bundle A+B by buying good A and good B separately, so your price for the bundle must be less than or equal to the sum of your prices for good A and good B.
Continuing the example from before, suppose you set price of good A = 50, price of good B = 50, and price of A+B = 75. What would a buyer who only visited you do? If the buyer bought A only, the buyer’s payoff would be 30 - 50 = -20. If the buyer bought B only, the buyer’s payoff would be 70 - 50 = 20. If the buyer bought A+B, the buyer’s payoff would be 100 - 75 = 25. If the buyer bought nothing, the buyer’s payoff would be 0. Since 25 is the biggest payoff for the buyer, this buyer would buy bundle A+B.

Buyers that visit all 4 sellers, do this calculation with each seller’s prices and then select the best option. Notice that the buyer could opt to not buy from you, but you only earn a profit if the buyer does buy something from you. Ties between sellers are broken randomly, but a buyer will buy the bundle if no other option yields a strictly higher payoff and a buyer will purchase as long as the buyer’s payoff is not negative.

“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 the bundle A+B. The region that is white represents buyers who would not buy given your prices.

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 the 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 bundle A+B. 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.
Appendix B. Comprehension Handout

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.

Example 1
The randomly determined buyer has Firm 1 sets the following prices:
Value of Good A = 30 Price of Good A = 45
Value of Good B = 40 Price of Good B = 55
Value of Bundle A+B = _______ Price of Bundle A+B = 95

The buyer’s payoff from Good A only =___, Good B only =___, and Bundle A+B =___
If the buyer only visits Firm 1, the buyer will purchase _____ and Firm 1’s profit = ____

Example 2
The randomly determined buyer has Firm 2 sets the following prices:
Value of Good A = 60 Price of Good A = 60
Value of Good B = 40 Price of Good B = 80
Value of Bundle A+B = _______ Price of Bundle A+B = 135

The buyer’s payoff from Good A only =___, Good B only =___, and Bundle A+B =___
If the buyer only visits Firm 2, the buyer will purchase _____ and Firm 2’s profit = ____

Example 3
The randomly determined buyer has Firm 3 sets the following prices:
Value of Good A = 60 Price of Good A = 60
Value of Good B = 40 Price of Good B = 55
Value of Bundle A+B = _______ Price of Bundle A+B = 65

The buyer’s payoff from Good A only =___, Good B only =___, and Bundle A+B =___
If the buyer only visits Firm 3, the buyer will purchase _____ and Firm 3’s profit = ____

Example 4
The randomly determined buyer has Firm 4 sets the following prices:
Value of Good A = 50 Price of Good A = 50
Value of Good B = 40 Price of Good B = 40
Value of Bundle A+B = _______ Price of Bundle A+B = 90

The buyer’s payoff from Good A only =___, Good B only =___, and Bundle A+B =___
If the buyer only visits Firm 4, the buyer will purchase _____ and Firm 4’s profit = ____
Example 5
The randomly determined buyer has
Value of Good A = 70
Value of Good B = 30
Value of Bundle A+B = _______

Firm 1 sets the following prices:
Price of Good A = 80
Price of Good B = 15
Price of Bundle A+B = 90

Firm 2 sets the following prices:
Price of Good A = 60
Price of Good B = 60
Price of Bundle A+B = 100

Firm 3 sets the following prices:
Price of Good A = 60
Price of Good B = 60
Price of Bundle A+B = 80

Firm 4 sets the following prices:
Price of Good A = 45
Price of Good B = 55
Price of Bundle A+B = 85

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