COSTLY BUYER SEARCH IN A DIFFERENTIATED PRODUCTS MODEL: AN EXPERIMENTAL STUDY

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Abstract

This study examines whether the content of buyer information and the timing of its dissemination affects seller market power. We construct laboratory markets with differentiated goods and costly buyer search in which sellers simultaneously post prices. The experiment varies the information on price or product characteristics that buyers learn under different timing assumptions (pre- and post-search), generating four information treatments. Theory predicts that price information lowers the equilibrium price, but information about product characteristics increases the equilibrium price. That is, contrary to simple intuition, the presence of informed buyers may impart a negative externality on other uninformed buyers. The data support the model’s negative externality result when sellers face a large number of robot buyers that are programmed to search optimally. Observed prices conform to the model’s comparative statics and are broadly consistent with predicted levels. With human buyers, however, excessive search instigates increased price competition and sellers post prices that are significantly lower than predicted.

JEL Classification: C91, D83, L13

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1. Introduction

Does improved product information always cause a positive externality for the buyers in the form of lower prices? The answer, surprisingly enough, is no. Stiglitz states “Improved information may affect the elasticity of demand facing the firm; if it increases the degree of monopoly power of each firm, it may lead to higher prices and lower welfare” (1979, p. 343). In this paper we use laboratory markets to investigate whether the content of information and the timing of its dissemination affect the sellers’ market power. Our main goal is to investigate the impact of improved buyer information on sellers’ pricing strategies. More precisely, we seek to attain empirical support for the prediction that improved product information may exert a negative externality on the buyers in the form of higher prices.

We examine price competition in a horizontally differentiated duopoly where buyers can engage in costly search. In the basic structure, all buyers are initially unaware of the prices or their valuations (hereafter, referred to as match value) for products sold by the two sellers and must engage in costly search to obtain this information. Theory predicts that improved buyer information can have differing effects on sellers’ market power, depending on its content - price or product attributes - and its timing - pre-search and post-search. Sellers are able to charge a higher price when the buyers are only informed about their match values (either pre- or post-search) as compared to the case where buyers have no information or when they have information about prices alone. Furthermore, sellers are able to charge a higher price if information about the match values is provided to the buyer before she begins the search process, thereby signifying the influence of the ‘timing’ of information dissemination. The intuition for these results is rather simple: A buyer who receives information about her match values from both sellers before she begins the search process will reveal this information by visiting the seller from whom she has a better match value (since she expects both sellers to set the same price). She will forego further search if price at the preferred seller exceeds the expected price by less than the search cost. This search behavior renders the demand less elastic and results in higher prices paid by all buyers. If however, information about the match value of the second seller is provided after visiting a seller, then the seller - whom the buyer has randomly chosen to search first - can no longer deduce that he offers the buyer a higher match and therefore, cannot exploit his advantageous position. This intensifies price competition since the seller will attempt to retain the buyer by offering her a better “price-match value”
combination. Similar reasoning entails that price competition is even more intense if the additional information available upon visiting one seller pertains to the price of the second seller.

The result that improved information may impart a negative externality is not new to the literature. Several articles have demonstrated that the value of information can be negative in multi-agent settings.\(^1\) Our results are in the same vein. However, our study contributes to the literature in two important ways: First, we provide a theoretical extension of Anderson and Renault’s (2000) model, which is itself based on Wolinsky (1986). Wolinsky was the first to introduce costly buyer search to a differentiated goods market. He examined a market setting where the buyers are aware of the availability of all the brands in the market but do not know either the prices or their match value from them. He concluded that costly search limits the ‘effective’ substitutability amongst brands, and gives the seller more market power which translates into supra-competitive prices. Anderson and Renault (2000) modify Wolinsky’s basic model of product differentiation to allow for heterogeneity in buyer information, and examine how improved product information can be a source of negative externality for the buyers. In this study, we extend their analysis by varying the informational conditions along two additional dimensions, and analyzing its impact on seller pricing behavior. Our model yields a rich set of comparative statics predictions.

Second, to the best of our knowledge, this is the first laboratory study of costly buyer search in a differentiated goods market. The prior literature on buyer search (e.g. Grether, Schwartz and Wilde 1988, Abrams, Sefton and Yavas 2000, Davis and Holt 1996, Cason and Friedman 2003, Cason and Datta 2006 and Cason and Mago 2008) has focused on homogeneous goods environment where paradoxically enough, the buyers should not search in equilibrium. Introducing product heterogeneity is important because it provides “search model with search.” The differentiated taste specification gives buyers a reason to search for a good which is a better match for their preferences, even when all sellers set the same price in equilibrium. Since buyer search is ubiquitous and truly homogenous goods as assumed in the theory are not,

\(^1\) Hirshleifer (1971) was the first to note that public information could make the agents worse off in a contingent contracts exchange economy. Mirman et al. (1994) shows that for a class of duopoly games with uncertain demand, public information about the demand parameters may have a negative value. Harrington (1995) finds the value of information about demand is negative for firms selling differentiated products. Some other articles that predict negative externality from improved information include Gal-Or (1988), Schlee (2001) and Sulganik and Zilcha (1996).
studying price competition and buyer search in a differentiated goods environment seems pertinent.\(^2\)

Our results also relate to the recent literature on advertising. Although we do not examine the mechanism by which the buyers receive information, our study can provide important insight into the role of advertising. For instance, in a recent paper Anderson and Renault (2006) evaluate a monopolist seller’s advertising decision under various information disclosure policies. They find that it is not necessary to impose a full disclosure policy for prices, and that the seller will choose to limit the information about its product attributes even when advertising is costless. Since forced disclosure of product attributes may be harmful to a seller, it gives the competitors an incentive to provide that information through comparative advertising. In a subsequent study, Anderson and Renault (2009) find that comparative advertising is used by weaker firms to target the market leaders and it reduces the overall social welfare. Our study contributes to this literature by providing an empirical analysis of market prices under exogenously specified informational conditions. A natural and straightforward extension of our experimental design is one that allows sellers to choose their advertising strategy pertaining to both price and match value information.

Our choice of laboratory methodology is guided by constraints imposed by both theory and availability of field data. Theoretical search models are often quite sensitive to their assumptions regarding information acquisition and dissemination. These assumptions tend to be highly stylized, detailed and often unrealistic, and cannot be easily adapted to accommodate industry-specific characteristics (Grether et al., 1988). Furthermore, their empirical assessment is impaired by lack of suitable field data. This problem is particularly evident when the goods are differentiated because field studies are limited in their ability to precisely measure consumers’ valuations for different attributes. Such estimation problems make the laboratory methodology particularly attractive, wherein there are no measurement errors and the basic underlying structural and informational conditions are known. Laboratory data is also untainted by various confounding factors that afflict the field data such as reputation formation and brand recognition.

\(^2\) Stigler states “there is never absolute homogeneity of commodities in naturally occurring markets” (1961, p. 213).
In order to capture the essential features of the conventional retail markets, in the laboratory we employ the standard posted offer trading institution. We vary the number and type (human versus automated) of buyers to provide both a rigorous test of the theory as well as outline its boundaries. We include treatments where robot buyers play a known equilibrium search strategy. This eliminates strategic uncertainty regarding buyers and allows the focus to be entirely on inter-seller competition. Incorporating human buyer population, on the other hand, provides a robustness check of the equilibrium price predictions to potential deviations from the optimal search behavior.

We have a rich panel dataset of pricing and search decisions of 200 subjects under different informational treatments across 20 sessions comprising of 72 periods each. The data from 16 robot buyer sessions indicate that the model predicts seller pricing behavior rather well. Observed prices conform to the model’s comparative statics and are broadly consistent with the predicted levels. The results from 4 additional sessions with human buyers, however, show systematic and substantial departures from the theory. We find that excessive search by human buyers instigates increased price competition and sellers post prices that are significantly lower than predicted.

The rest of the paper is organized as follows: Section 2 describes the theoretical model, and provides examples to motivate the different informational treatments. Section 3 describes the experimental design and the empirical results when sellers face stable, equilibrium-playing robot buyers. Section 4 includes a similar analysis for markets where sellers face human buyers who may or may not engage in optimal search. We split our analysis for the two buyer populations because of the drastic difference in the results. Section 5 concludes.

2. Theoretical model

The theoretical structure underlying the various informational treatments has a common layout. For simplicity of exposition, we begin with the case of uninformed (UI) buyers, which is essentially Wolinsky’s (1986) model in a duopoly setup. Figure 1 shows the game tree for this baseline model.

Consider a market where two sellers, 1 and 2, sell a variant of a horizontally differentiated product. Sellers face no capacity constraints and compete by simultaneously setting prices, \( p_1 \) and \( p_2 \). Production cost is the same for both sellers and is normalized to zero. On the demand
side, we assume that there is a continuum of buyers, each of whom can buy a single unit of the differentiated good from either seller 1 or 2. Buyers differ with respect to their tastes for the products of the two sellers, or in other words, each buyer has match values that differ intrinsically across the two sellers. These match values \([\varepsilon_{1i}, \varepsilon_{2i}]\), for each buyer \(i\) and both sellers 1 and 2, are assumed to be i.i.d random variables from a uniform distribution function \(F\) which has finite support \([a, b]\) with \(a>0\).\(^3\) Although the distribution of match values is common knowledge, before making their pricing decision sellers do not know the exact match values that the buyers receive from their product.

We assume that, a priori, all buyers are uninformed about the prices or their match values from the two sellers, and gather this information by searching at a constant search cost, \(c\), per seller. The search is without replacement and with perfect recall. The buyer must visit a seller in order to make the purchase, and the total search cost is \(c\) for a buyer who stops searching after the first seller and \(2c\) for a buyer who searches both sellers. Buyer \(i\)’s indirect utility conditional on purchasing the good from seller \(j\) at price \(p_j\) (not accounting for search costs) is
\[
\nu_{ij} = y - p_j + \varepsilon_{ij}
\]
where \(y\) is the common budget constraint and \(p_j \in [0, y]\). We allow buyers no outside option.

We focus our attention on symmetric equilibria in pure strategies.\(^4\) Consistent with the previous literature, we consider the perfect Bayesian Nash equilibrium. This means that sellers maximize their expected profit given the price set by their rival and the optimal buyer search behavior; and buyers maximize their expected utility taking into account the previously observed prices and match values, and the expectation of the unknown prices and match values. In equilibrium, buyer’s price expectations are consistent with the sellers’ strategies and remain unaffected by previously observed prices; thus, in equilibrium, a buyer always expects the sellers to set the equilibrium price \(p^*\).

To characterize the pure-strategy symmetric equilibrium, we begin by analyzing the decision problem of a buyer. We assume that the buyer engages in optimal sequential search. That is, in her decision to search the second seller the buyer weighs the expected benefit against the cost

\(^3\) The i.i.d assumption implies that aggregate preferences are symmetric - the number of buyers who prefer seller 1 to seller 2 equals the number of buyers who prefer seller 2 to seller 1; and buyer \(i\)’s match value from seller 1 is independent of her match value from seller 2.

\(^4\) Refer to Anderson and Renault (2000), footnote 12, p. 728 for the conceptual difficulties in formulating an asymmetric equilibrium.
of additional search. This tradeoff allows us to uniquely define a critical reservation value, $x'$, such that a buyer who receives match value $x'$ from the first seller she sampled is indifferent between purchasing from that seller and searching the other seller.\textsuperscript{5} $x'$ is defined as follows:

$$\int_{x'}^{b} (\epsilon - x') f(\epsilon) d\epsilon = c$$ \hfill (2)

A buyer’s optimal sequential search rule can then be characterized as follows: A buyer searches one of the two sellers at random, expecting that both sellers set price $p^*$.\textsuperscript{6} Suppose buyer $i$ searches seller 1 first, and upon visiting seller 1 learns $p_1$ and $\epsilon_{i1}$. The buyer then decides to either purchase from seller 1 or visit the second seller. In her decision to search again, buyer $i$ takes into account the expected price premium ($p_1 - p^*$) (calculated accounting for the fact that in equilibrium, the buyer continues to hold the belief that seller 2’s price is equal to $p^*$) and the expected difference in match values. Buyer $i$ will search seller 2 only if

$$y - p_1 + \epsilon_{i1} < y - p^* + x'$$ \hfill (3)

If buyer $i$ chooses to visit seller 2 she learns $p_2$ and $\epsilon_{i2}$, and then simply purchases from the seller whose good yields a higher utility, i.e. buyer $i$ purchases from seller 1 if

$$y - p_1 + \epsilon_{i1} > y - p_2 + \epsilon_{i2}$$ \hfill (4)

In order to avoid trivial cases, we consider the case where the critical value $x'$ is greater than $a$, the lower bound of the match values distribution.\textsuperscript{7}

The buyer’s optimal search equation is then used to construct the expected demand addressed to each seller. In the symmetric equilibrium, $p_1 = p_2 = p^*$, each seller sells half the aggregate demand and earns equal profit.\textsuperscript{8}

We use this basic framework to examine three other informational structures. In each of these cases, there are 2 types of buyers. A fraction $(1-k)$ of the buyers are similar to those considered above. That is, they are a priori uninformed, and upon visiting a seller learn only the

\textsuperscript{5} “The advantage of reservation price approach is that it allows us to view a complicated oligopoly problem from a monopoly perspective. It enables us to prove existence of oligopoly equilibrium without discussing any specific interactions between firms.” (Caplin and Nalebuff, 1991, p. 35).

\textsuperscript{6} Given the symmetry in the distribution of match values, half of the buyers begin searching at each seller.

\textsuperscript{7} Note that no buyer will search the second seller if $x' < a - (p_1 - p^*)$. Similarly if $x' < a$, buyers will search again only if they anticipate a large enough price difference. These cases represent the Diamond Paradox because the only Nash equilibrium for all sellers is to price at the budget constraint $y-c$. At any price lower than $y-c$, sellers can raise price (and profit) without losing any customers. The $x' > a$ condition can be obtained by putting a restriction on the maximum possible value of the search cost.

\textsuperscript{8} The assumption that the match values are i.i.d uniform ensures that the each seller’s profit is a quasiconcave function of its own price, and thereby guarantees the existence of the equilibrium in pure strategies.

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price and their match value from that seller. For the remaining $k$ ‘informed’ buyers, the informational structure differs in terms of the timing of information dissemination and the content of information available upon each search. The assumptions on buyer information and the resulting optimal search rule for these $k$ ‘informed’ buyers are outlined below.\(^9\) Without loss of generality, suppose informed buyer $i$ visits seller 1 first.

**Price Informed (PI):** Upon visiting seller 1, buyer $i$ learns $p_1$ and $\varepsilon_{i1}$ (like fraction $1-k$ uninformed buyers), and in addition she also learns the price set by seller 2, $p_2$. She must however pay the additional search cost to visit seller 2 in order to learn her match value $\varepsilon_{i2}$. For such ‘price informed’ buyer, the decision to search seller 2 is optimal if

$$y - p_1 + \varepsilon_{i1} < y - p_2 + x'$$

(5)

The PI structure reflects market situations where price comparisons are provided by the seller (perhaps, as an advertising device) but the buyer must still search in order to ascertain the exact suitability of the product to her specific needs.\(^10\) Even in case of online sites such as Progressive.com (insurance) which provide ‘one stop’ comparative price information, the buyer needs to search other providers in order to obtain the precise product details.

**Match Informed (MI):** Upon visiting seller 1, buyer $i$ learns $p_1$ and $\varepsilon_{i1}$ (like fraction $1-k$ uninformed buyers), and in addition she also learns her match value from the good sold by seller 2, $\varepsilon_{i2}$. She must however pay the additional search cost to visit seller 2 in order to learn the price of seller 2, $p_2$. For such ‘match informed’ buyer, the decision to search seller 2 is optimal if

$$y - p_1 + \varepsilon_{i1} < y - p^* + \varepsilon_{i2} - c$$

(6)

The MI structure considers the case where during the course of a sales pitch, the buyer receives not only information about the product of that seller but also learns the product attributes of the rival seller. For instance, a real estate agent not only provides information about her apartment complex but also how its location compares to others. Similarly, a Toyota car salesman may

\(^9\) The value of $p^*$ depends on the type of informational structure, but to simplify the notation we do not define an information-specific equilibrium price.

\(^10\) Retail stores like Wal-Mart routinely display “Dare to compare” prices.
provide information about a comparable model by Honda. However, the buyer must still visit
the second seller (Honda) in order to negotiate the final sales price.

**Pre-Search Match Informed (PSMI):** This treatment corresponds to Anderson and Renault
(2000) which assumes that a fraction \( k \) of the buyers learn about their match values from both
sellers before engaging in any search. Since buyers expect both sellers to set the same price,
and since the distribution of match values is assumed to be symmetric, \( k/2 \) buyers visit each
seller. This means that a ‘pre-search match informed’ buyer \( i \) who expects both sellers to set the
same price, first visits a seller from whom his match value is higher. If \( \varepsilon_{i1} > \varepsilon_{i2} \) buyer \( i \) first
visits seller 1 and learns \( p_1 \). The decision to search seller 2 is optimal if

\[
y - p_1 + \varepsilon_{i1} < y - p^* + \varepsilon_{i2} - c
\]

The PSMI structure captures instances where the buyers have a well-defined conception of the
value they attach to the product but may be unaware of its exact price. The field counterpart for
such an informational environment includes products such as vacation destinations or antiques.
In other cases, print or audio-visual media may costlessly inform buyers prior to search about
their relative match values from different sellers.\(^{11}\) The buyers must then incur costly search in
order to obtain the price information.

Note that in all four cases, the optimal search strategy is contingent on the information
available after searching the first seller. In the Uninformed treatment, optimal sequential search
takes into account the *expected* price premium \((p - p^*)\) and the *expected* difference in match
values. In the Price Informed treatment, the search decision is based on the *known* price
premium and the *expected* difference in match value while in the Match Informed treatment,
the search decision is based on the *known* difference in match values and the *expected* price
premium. The optimal strategy for second search is identical in the Match Informed and Pre-
Search Match Informed cases, and the difference lies only in the initial search rule. The
informed buyers of the PSMI treatment always begin by searching the seller with the higher
match value.

Table 1 summarizes the buyer’s optimal search and purchase rules for all four informational
treatments. These differing buyer search strategies then translate into differing seller pricing

\(^{11}\) For example, a calorie conscious consumer may be informed about the relative dietary benefits of a particular
food choice (Subway versus McDonalds) or a patient might be informed about the relatively low side effects of a
particular drug (Tylenol versus Bayer).
strategies. Proposition 1 summarizes the symmetric price equilibrium in pure strategies for all four informational treatments. The formal statement and the proof of the proposition appear in Appendix A. Here, we concentrate on the comparative statics that are central to our experimental design. In equilibrium, prices in the different informational structures can be ranked as follows:

\[ PI < UI < MI < PSMI \]  

(8)

The most striking feature of these equilibrium comparative statics is that they are in sharp contrast to the usual economic reasoning of the positive externality imparted by the more informed consumers. First, informational content matters. Improved buyer information about prices increases the sellers’ incentive to engage in price competition and exerts a downward pressure on the equilibrium price.\(^{12}\) However, we find that while price information lowers the equilibrium price, match information irrespective of the time of its provision increases the equilibrium price. The match-informed buyers search less than the price-informed or the uninformed buyers, making the demand more inelastic and granting the sellers additional market power. Second, the timing of information dissemination matters. If some of the buyers are informed about their match values prior to search, the elasticity of a seller’s expected demand is reduced by exactly that proportion since only the proportion of the demand addressed by uninformed buyers is price sensitive. For instance, if all buyers are informed about their match values prior to search, sellers charge the maximum price that the buyers can afford, \( y-c \).

Table 2 presents the theoretical predictions for our chosen experimental parameters. Note that unlike a homogeneous goods environment where the presence of differentially informed buyers yields price dispersion as the equilibrium outcome; in our differentiated goods setting there is a unique market price. In all treatments, the market price is bounded away from the monopoly price (185) because in equilibrium, buyers search for a better match value. Costly search, however, entails that the improved buyer information alone is not sufficient to drive prices down to the competitive level (50).\(^{13}\)

\(^{12}\) Grossman and Shapiro (1984) who analyze price advertising in a differentiated products framework also find that prices decline as advertising costs decreases and more buyers get informed.

\(^{13}\) The monopoly case is similar to PSMI treatment with \( k = 1 \). The buyer will visit the monopoly seller (or higher match value seller in PSMI) and will buy from that seller if \( p \leq \min \{y-c, y+\varepsilon-c\} \) where \( \varepsilon \) is the realized match value. Since \( \varepsilon > 0 \) by assumption, the monopolist can charge the highest possible price, i.e. \( p^* = y-c \). The no search cost, complete information price is derived using Perloff and Salop (1985, p.110, equations 12 and 13).
3. **Experiment 1: Robot Buyer Sessions**

We begin by creating an environment that is most conducive for the theory to work. The theoretical model calls for a continuum of buyers which in experimental settings can be approximated by simulating buyers with computer algorithms or ‘robots’. The treatment in which a large number of robot buyers play a known equilibrium search strategy eliminates the extraneous variability arising from sample variance and buyer idiosyncrasies and allows the focus to be entirely on seller behavior that is central to the theory.

### 3.1 Design and Procedures

*Experimental Design:* Table 3 summarizes the experimental design. 16 subjects, all sellers, comprised one experimental cohort. To mitigate the repeated game effects, we randomly re-matched sellers each period. We divided each cohort into two equal sized sessions of 8 sellers each, and the random matching took place within each session. This allowed us to run two simultaneous sessions and obtain two statistically independent observations from each cohort.

Each experimental session consisted of three sequences of 24 periods each. The first sequence always constituted of the baseline UI treatment. To study the impact of different informational conditions on sellers’ pricing strategy, we included two other informational treatments where the proportion of informed buyers, \( k \), was exogenously set at 0.5. Having the same set of subjects make decisions under three different treatments has the advantage of directly controlling for subject variability, and allows the effect of change to be assessed by within-session comparisons. The drawback of such a design, however, is that experience in one of the conditions may systematically affect the subjects’ choice in the ensuing conditions. Switching the order of the informational treatments helped measure and control for these experience effects. For instance, four sessions featured “UI- PI- MI” treatment sequence, and the ordering of the last two sequences is reversed in the other four sessions (UI- MI- PI). A similar design pattern is used for sessions including the PSMI treatment.

*Experimental Procedures:* We report results from 16 robot buyer sessions which were conducted in the Vernon Smith Experimental Economics Laboratory at Purdue University. Subjects were recruited from introductory undergraduate economics classes. A computerized interface using the software z-Tree was used to implement the experimental environment (Fischbacher, 2007). General trading instructions were read aloud at the beginning of the
experiment, and new instructions pertaining to the relevant informational treatment were read at the beginning of each sequence. Throughout the session, no communication between subjects was permitted and all choices and information were transmitted via computer terminals. The transactions in the experiment were in terms of francs, which were converted to real dollars at the end of the experiment using a known conversion rate. Each experimental session lasted about 2 hours and the earnings ranged from $20 to $32.14

The experiment was instituted as a Posted Offer market with 2 sellers and 200 robot buyers in each market. Sellers had zero production costs and no capacity constraints. Buyers were endowed with an identical income level of 200 francs in each period that capped their willingness to pay. Sellers were not allowed to post a price greater than this maximum. Buyer search cost was kept constant at 15 francs in all sessions.

In each period, every buyer received a pair of match values – one from each duopolist. These match values were independent, computerized draws from a uniform distribution in the set \{10, 10.01, \ldots, 110\}. It was made clear to the subjects that the match values received by the buyers were not a choice variable i.e. they did not depend on the actions of the participants in the experiment, nor on the match values drawn by other buyers or the match values drawn in other periods. Depending on the treatment, half of the buyers also received additional information. Every buyer was equally likely to receive this information, and the actual distribution of informed buyers was randomly determined by the computer software. Finally, the reservation value strategy which determines the buyers’ search decision was known to all the sellers in the market. In the instructions (Appendix B) we provide detailed examples illustrating different scenarios and highlighting the differences across treatments.

The trading in each period proceeded as follows: Sellers simultaneously post prices. After both sellers made their pricing decision, the robot buyers searched according to the equilibrium search strategy. Half the robot buyers were randomly assigned to each seller, i.e., they first search the assigned seller.15 At the end of the trading period, sellers received information about their profit, the price posted by the paired seller and the average match value received by the buyers initially assigned to him and to the paired seller. At the beginning of the next trading

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14 At the beginning of each sequence subjects also received a starting balance of approximately $1.
15 The sole exception is the \(k\) informed buyers of the PSMI treatment. Since they receive the match value information of both sellers prior to search, they always chose to first search the seller with a higher match value.
period, sellers received a history table detailing their average match values, prices and profits in all the previous periods.

3.2 Results

The robot buyer experiment provides a panel dataset of pricing decisions under different informational treatments for 72 periods across 16 sessions and 64 markets. Overall, prices exhibit the predicted pattern and appear to conform to the model’s comparative statics predictions. The fact that prices in each session move in accordance to the directional prediction of the model is evident from Figures 2-5. Formal statistical analysis discussed below provides a more rigorous support to the visual impression gleaned from the graphs. Our focus is primarily on testing the model’s comparative statics predictions and on the equilibrium quantitative comparison. To account for the treatment switchover effect and the possible hysteresis effect, we restrict our analysis to the data from the last 10 periods of each run.

3.2.A Comparative statics

Table 4 presents the mean price in the last 10 periods. We have 16 independent observations for the UI and MI treatments and 8 independent observations for the PI and PSMI treatments.16

The non-parametric Wilcoxon Sign Rank test rejects the null hypothesis that prices are same across different informational treatments. For instance, 15 out of the 16 pairwise differences obtained from the comparison of MI and UI treatment are positive (p-value < 0.01) which implies that price in the MI treatment are significantly higher than price in the UI treatment, as predicted by theory. A similar comparison of price in the MI treatment with the PI and PSMI treatment prices produces signs that are all in favor of the directional alternative predicted by the model - price in PI < MI < PSMI.17 The only ranking that is inconsistent with the equilibrium prediction is that of UI and PI prices. We find that the difference are not statistically significant (p-value = 0.09). This divergence may partly be explained by the sequence ordering, and hence experience. The mean price in the UI treatment always exceeds

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16 As noted earlier, random re-matching is an important part of our design. However, this design choice limits the number of statistically independent observations generated by each group of subjects.

17 In fact, all of the 8 pairwise differences favor the theoretical prediction (p-value < 0.01). The results are the same when sign test was employed for these within-session comparisons. Independent across-session comparison using the Mann-Whitney test also finds support for the model’s comparative statics predictions (p-value < 0.05).
that of the PI treatment when PI treatment immediately follows the UI treatment. However, in 3 out of 4 cases where PI is the last sequence (preceded by a higher-priced MI treatment), the mean price in the PI treatment exceeds that of the UI treatment.\(^{18}\)

Since sequence order effects are difficult to control using non-parametric methods, we employ panel data econometric models that include random effects for subject-level price choices and fixed effects for session-level analysis of treatment ordering. The estimates are corrected for heteroscedasticity and include control for time trend. The regression equation for a given informational treatment \(a\) is

\[
p_{i,t} = \alpha + \beta_D^{p_j} + \beta_s D_t^s + \beta_t D_t^t + \beta_4 (1/t) + \delta d + \lambda s + \epsilon_{i,t} \tag{9}
\]

\(p_{i,t}\) is subject \(i\)'s price in period \(t\)
\(D_t^j = 1\) if \(p_{i,t}\) comes from treatment \(j \neq a\) and \(D_t^j = 0\) otherwise
where \(d\) is a vector of session dummies
\(s\) is a vector of sequence dummies
\(\epsilon_{i,t}\) is the composite error term.

The coefficients on the treatment dummies indicate whether prices differed in those treatments compared to treatment \(a\). Analogous to the non-parametric results, the null hypothesis that prices are the same across different informational treatments is rejected at any conventional level of significance for all pairwise comparisons. The regression results show that all treatment dummies are significant and have the predicted sign. In fact, even the UI-PI equality can be rejected at conventional level of significance. Despite concentrating on the last 10 periods of each treatment run, we find the time trend to be significant (p-value < 0.05) indicating that learning is an ongoing process. The sequence dummy is also significant, consistent with the non-parametric results discussed above.

Hence, based on both parametric and nonparametric methodology, prices can be empirically ranked as follows:

\(^{18}\) The impact of sequence ordering on the subjects’ decisions is also evident in the MI treatment. Unlike PI and PSMI treatment, MI treatment was conducted in all sessions, half the time as the second sequence and half the time as the last sequence. We find that prices are consistently above the equilibrium prediction when MI treatment was preceded by a higher price prediction treatment viz. PSMI. On the other hand, when either UI or PI treatment preceded the MI treatment, prices are below the predicted level. Further, MI prices are always higher when it is the last treatment sequence in a session, so the Mann-Whitney test rejects the null hypothesis that MI prices are equal irrespective of their order in the sequence of treatments (p-value = 0.01, n=m=8).
This ranking supports all the comparative statics hypotheses of the model. Thus, we conclude that both the content of information and the timing of its dissemination matter for price formation in search markets with differentiated goods.

3.2.B Equilibrium quantitative comparison

Next, we turn to a more demanding test of the theory. By comparing the observed prices to their equilibrium values, we are able to assess the ability of the model to predict the pricing behavior observed in the laboratory. The panel data regression equation used for this comparison can be stated as follows:

\[ p_{i,t}^a - p^a = \alpha + \beta(1/t) + \delta d_i + \lambda s_i + \varepsilon_{i,t} \]

where \( p_{i,t}^a - p^a \) is the difference between subject \( i \)'s price in period \( t \) and the equilibrium prediction for treatment \( a \), \( d_i \) is a vector of session dummies, \( s_i \) is a vector of sequence dummies and \( \varepsilon_{i,t} \) is the composite error term. Regression results indicate prices in the UI, PI, and PSMI treatments are not significantly different from their treatment-specific prediction while price in the MI treatment is significantly lower than predicted (p-value=0.02). Our quantitative hypothesis that the PSMI price is twice the UI price also finds strong support in the lab (chi-square = 1.9, p-value = 0.17).

Finally, we study the process of convergence. Price dispersion, defined as the variance of posted prices across all sellers, should asymptotically approach zero as subjects gain experience in a particular treatment run. Using price variance as the dependent variable, we apply a convergence model specification first used by Noussair et al. (1995). For each informational treatment, we estimate the following regression equation

\[ v_{i,t} = \sum_{i=1}^{l} D_i \left( \beta_{ot} \frac{1}{t} + \beta_{it} \frac{t-1}{t} \right) + u_{i,t} \]

where \( i = \{1, \ldots, j\} \) indexes the session and \( t \) denotes the time period. The dummy variable \( D_i \) takes a value of 1 when the observation is from session \( i \). This model specification shifts the prediction weight from the starting point to the asymptote in the later periods. Thus, for each
session \( i \), \( \beta_{ot} \) reflects the predicted variance at the beginning of the treatment run and \( \beta_{ft} \) indicates the predicted asymptote in the final period.

We find that price dispersion remains significantly positive even asymptotically. However, for all sessions \( \beta_{ft} \) term is closer to zero than the corresponding \( \beta_{ot} \) term indicating a clear decline in the variance over time. An F-test of the restriction \( \beta_{ot} = \beta_{ft} \) is rejected all 16 times for the UI treatment, and 10 out of 16 times for the MI treatment. Equality of the initial and final variance asymptote is rejected in 5 out of 8 sessions of the PI and PSMI treatments. Finally, the decline in variance tapers off. When we restrict the analysis to the last 10 periods, the \( \beta_{ot} = \beta_{ft} \) equality is rejected only 4 and 5 times (out of 16) in the UI and MI treatment, respectively. The proportion remains unchanged for the PI and PSMI treatments.

The results from the robot buyer sessions can be summarized as follows:

**Result 1:** The comparative statics predictions of the model hold. Prices can be empirically ranked as PI \( \leq \) UI < MI < PSMI.

**Result 2:** Prices converge to the treatment-specific equilibrium prediction with the exception of MI prices which are, on average, lower than predicted. Variance of prices declines over time but does not converge to zero.

4. **Experiment 2: Human Buyer Sessions**

Holt (1995) conjectures that “under posted-offer rules, natural markets with large number of small buyers are best approximated by simulated buyers in the laboratory” (pg. 381). Our results from the robot buyer sessions indicate that the sellers best respond to the optimal search behavior of the buyers, but what happens if buyers behave sub-optimally? A fundamental assumption made in the robot buyer sessions is that price expectation remains unaffected by repeated observation of non-equilibrium prices; and while this assumption is consistent with the rest of the search literature, it may not hold in practice. The human buyers have no reason to maintain unrealistic beliefs about the equilibrium price distribution and adhere to a fixed equilibrium reservation price strategy. They can instead update their beliefs and search strategies when they observe lower prices in the early periods. Hey (1982) was the first to state that most subjects follow a sort of self-imposed reservation rule, wherein “they stop search if a
price quote is received that is ‘sufficiently’ low” (pg. 72). Moreover, “human buyers might not follow strictly a reservation price strategy, much less (an) identical reservation strategy” as noted by Cason and Friedman (2003, p. 239). This heterogeneity in buyer behavior is bound to influence the sellers’ pricing strategy. Furthermore, this process can be self-perpetuating: Differing seller experience encourages differing pricing behavior, which in turn encourages differing search strategies by the buyers. Hence it is important to test whether the model’s price predictions are robust to deviations from the optimal risk neutral buyer search strategy.

Our choice of buyer population as a treatment variable is also informed by the mixed results obtained by prior laboratory studies. A dramatic difference in outcomes between the automated and human buyer treatments has not been observed in some of the previous posted offer experiments with costly buyer search (Cason and Friedman, 2003) and without search (Davis and Williams, 1999). Coursey et al. (1984) and Brown-Kruse (1991), on the other hand, present a comparison of human buyers with computer simulation of demand in contestable market experiments. Both studies find that the mere potential for demand withholding imparts greater disciplining power to the buyers, and hence faster convergence to the competitive equilibrium is observed in the presence of human buyers.19

Closer to this paper are studies by Cason and Datta (2006) and Cason and Mago (2008). Both studies consider a homogeneous goods model that embodies both buyer search and seller advertising, and the only difference lies in the type of buyers. The robot buyers sessions reported in Cason and Datta (2006) provide uniformly positive support for the theoretical dispersed-price equilibrium but the human buyers sessions in Cason and Mago (2008) feature excessive search and Bertrand-like pricing strategy. In our setting, product differentiation should prevent prices from falling to marginal cost but the underlying behavior – excessive buyer search and information gathering – is likely to remain the same. Hence, parallels can be drawn between these studies.

The next section describes the laboratory environment where sellers interact with a finite number of human buyers. It is important to emphasize that the environment is not intended to be a precise test of theory (as noted above, the model predicts well with equilibrium playing

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19 The fact that human buyers are more apt at extracting surplus compared to human sellers is also evident in the comparison of posted-offer versus posted-bid experiments (Holt, 1995, pg. 378).
robot buyers), but instead provides evidence of the model’s empirical value when confronted with possibly disequilibrium search behavior.

4.1 Design and Procedures

We report 4 sessions that examine the market outcome with human buyers. In terms of experimental design, we restrict ourselves to the analysis of pre- and post-search match information treatments. Session 1 employs UI-MI-PSMI ordering and Session 2 employs UI-PSMI-MI ordering. In session 3, we repeat the ordering of session 1 but employ a higher conversion rate to increase the penalty for deviating from the equilibrium. Session 4 employs PSMI-MI-UI ordering. Experimental procedures across the robot and human buyer sessions were kept as parallel as possible with the following exceptions: Unlike the robot buyer sessions where all 8 subjects were sellers, the 18 subjects in each human buyer session were divided to form 3 duopoly markets with 4 buyers in each market. The subjects were randomly assigned the role of either a buyer or a seller and their role remain unchanged for the entire length of the experiment. The random matching process involved both types of agents; i.e., in each period there was a new random allocation of buyers and sellers to each market. At the end of the period, buyers were informed about the match value they received, and the price and search cost they paid.

4.2 Results

Figures 6 and 7 display the time series of mean prices and orient the discussion in this section. The figures clearly show that while price in the UI treatment tends towards the equilibrium prediction, MI and PSMI treatment prices are low and show no sign of convergence. The summary statistics (Table 5) not only indicate the level of divergence from the equilibrium but also reject the comparative statics predictions of the model.20

It is plausible that the observed invariance in price is simply a result of path dependence. In such a case, price would be higher if the first sequence comprised a higher-predicted-price PSMI treatment. To eliminate path dependence as a possible explanation, we conduct a session

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20 A comparison of the average price in sessions 1 and 3 (Figure 12) reveals no significant change in results. Although the overall price level is slightly higher in session 3 compared to session 1, it still does not respond to the change in informational treatments.
with PSMI-MI-UI ordering (session 4). Figure 8 displays average price that starts high but quickly converges to a level similar to the previous sessions.

While there is little economic difference in the price across different informational treatments, to assess the statistical significance of these results, we use the parametric methods described in the previous section. As earlier, the panel nature of the dataset is modeled with subject-specific random effects and session-level fixed effects, and the analysis is restricted to data from the last 10 periods. The regression results show that prices do not conform to the model’s comparative statics prediction. Price in the MI treatment is significantly lower than the price in the UI treatment (p-value < 0.01); while the PSMI price is not significantly higher than the UI price (p-value > 0.05). The price can therefore be ranked as follows:

$$MI < UI = PSMI$$ (13)

Furthermore, equilibrium quantitative comparison yields that price observed in the last 10 periods of the UI treatment is not significantly different than predicted; but price in both MI and PSMI treatments is lower than the treatment-specific prediction (p-value < 0.01). The variance in posted prices declines over time in most informational sequences but never converges to zero. Analogous to the robot buyer sessions, the decline in variance tapers off.

The failure of the model to accurately predict the market outcome in case of human buyers calls for further investigation. We need to ascertain the reason for the observed deviation from the equilibrium outcome and whether the decisions on either side of the market account for these deviations. Therefore, in the next subsection we detail buyers’ search decisions and examine their impact on sellers’ pricing decisions.

### 4.3 Buyer search behavior and Seller pricing decisions

Figure 9 presents the observed propensity to search in different informational treatments. While the search propensity is almost identical in the UI (45.6%) and MI (46.3%) treatments, prior information of match values does curtail some buyer search in the PSMI (32.1%) treatment. Theoretically, ‘optimality in search’ is defined in terms of equilibrium reservation value strategy. However, evaluating the effectiveness of buyer search behavior without accounting for obvious seller deviations from the equilibrium price predictions will surely yield

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21 Unlike the automated buyer treatment, each human buyer session yields only one independent observation. Given the paucity of data, the non-parametric tests will not have sufficient power.
a distorted picture of the actual behavior. To account for such pitfalls, we consider two extreme benchmarks for the belief a buyer places on the price of the other seller: Cournot expectations (average price observed last period) and Fictitious Play expectations (average of all previously observed prices). Figure 9 shows that irrespective of the process of belief formation, the observed search propensities are high, and there is substantial and systematic deviation from the predicted search behavior.

When buyers fail to search optimally, it is useful to divide their mistakes into two types of errors: undersearch and oversearch.

Type 1 error (undersearch): Subjects did not search when they should have searched, i.e., the value obtained upon search would have been higher.

Type 2 error (oversearch): Subjects searched when they should not have, i.e., the additional search did not yield a higher value.

As above, we use the three benchmark price predictions – equilibrium, Cournot and Fictitious play - to compute the expected value obtained upon search. Table 6 shows that irrespective of the process of belief formation subjects in the MI and PSMI treatment tend to err on the side of oversearch (Type 2 error). This result is inconsistent with the previous literature on sequential search where the pattern of error exhibits a bias towards stopping too soon (e.g. Schotter and Braunstein, 1981; Hey, 1987; Cox and Oaxaca, 1989; Sonnemans, 1998; Cason and Mago, 2008).22

To provide insight into the factors that influence buyer search decision across different informational treatments we employ parametric modeling techniques. Table 7 presents the estimates of probit regressions that assume subject-level random effects specification for the error term. The dependent variable is a dummy variable equal to 1 when buyer i searches the second seller, and 0 when the buyer foregoes additional search to purchase from the assigned seller. We find that buyers visit the second seller if price at the assigned seller is high but by the same token, they forego additional search when the match value of the assigned seller is high.23 Consistent with the theoretical model, informed buyers search less compared to uninformed buyers. Compared to the UI treatment, search frequency is significantly lower in the PSMI

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22 With the exception of Cason and Mago (2008), all other studies have examined a simpler problem of sequential search for a price (or wage) given a fixed and known price (or wage) distribution. In a market setting, however, there is endogenous determination of prices by the sellers.

23 In case of the PSMI treatment, ‘assigned match value’ is defined as the higher of the two values revealed to the buyer prior to search. Only 0.3 percent of the PSMI buyers began by searching the seller with a lower match value.
treatment and it is significantly higher in the MI treatment. For most part, search behavior is invariant to time. If anything, frequency of searching the second seller declines over the first 15 periods and stabilizes thereafter.

The next obvious question to ask is whether these low prices are in fact the sellers’ best response given the buyer search behavior, i.e., can the large difference between the observed and optimal search behavior explain the large difference between the observed and equilibrium price outcome. To analyze this, we begin by calibrating the probabilistic buyer search rule for each informational treatment. We use the probit search estimates in Table 7 and set all explanatory variables at their sample means to trace out the search probabilities for different levels of observed prices. These buyer search probabilities are then used to compute an approximation of the ‘probabilistic demand’ curve facing a seller. For each treatment $i$, an approximate ‘probabilistic demand’ curve facing the (assigned) seller $a$ when she sets price $p_a$ is calculated using the following equation:

$$D^i_a(p_a, p_b) = [0.5 \times (1 - s_i(p_a)) + s_i(p_a) \times r_i] + 0.5 \times s_i(p_b) \times (1 - r_i)] \times 4$$ (14)

where $s_i(p_a)$ is the probability of searching the second seller $b$ in treatment $i$ and $r_i$ is the empirical recall propensity in treatment $i$ or the average percentage of times a buyer purchased from the first seller after searching the second seller.

Table 5 summarizes the sellers’ best response price for different informational treatments along with the observed and equilibrium price prediction. The best response prices are clearly not very different from the observed prices, rather they preserve the observed price ranking. This indicates that seller pricing behavior is reasonable when we account for the excessive search by the human buyers.

The results from the human buyer sessions can be summarized as follows:

**Result 3:** The comparative statics predictions of the model do not hold. Prices can be empirically ranked as MI $< UI \approx$ PSMI.

**Result 4:** UI prices converge to the treatment-specific equilibrium prediction but prices in the MI and PSMI treatments are significantly lower than predicted. Variance declines over time.
Result 5: Human buyers tend to over-search, which intensifies price competition among sellers. The low prices are approximately equal to the sellers’ best response given the observed buyer search behavior.

5. Conclusion

In most retail markets and for most products, information about both prices and product attributes is imperfect. This study extends the experimental literature on costly buyer search to markets with differentiated products. The question of primary interest is whether the content of buyer information and the timing of its dissemination affects sellers’ pricing behavior. Better knowledge of the welfare implications arising from these kinds of the informational imperfections can provide a sounder basis for policy reforms. For instance, various consumer protection regulations stipulated by the Federal Trade Commission that are aimed towards curbing the harms of ‘imperfect information’ should take into account the nature of informational imperfection and not just its mere existence.

We construct laboratory markets based on the key features of a price-setting, differentiated goods duopoly model analyzed by Wolinsky (1986) and Anderson and Renault (2000). In each market, sellers simultaneously post prices, while buyers engage in costly sequential search to obtain information from a seller and complete their purchase. The experiment varies the information on price or product characteristics that buyers learn under different timing assumptions (pre- and post- search), generating four informational treatments. Theory predicts that price information lowers the equilibrium price but information about product characteristics increases the equilibrium price, irrespective of the time of its provision.

Our experiment provides mixed support for the theoretical model. The laboratory data support the negative externality prediction when sellers face a large number of robot buyers that are programmed to search optimally. The observed prices conform to the model’s comparative statics and are broadly consistent with the predicted price levels. With human buyers, however, the data clearly indicate a systematic departure in the direction of more competitive pricing behavior than the theory predicts. Our analysis suggests that the excessive search by human buyers instigates increased price competition amongst sellers; and thus the aggressive pricing behavior is a rational response by the sellers to the observed buyer search behavior.
References


Appendix A

Proposition 1: Suppose $\varepsilon_j$ is uniformly distributed over the interval $[a, b]$, $j = 1, 2$, search cost $c$ satisfies $0 < c < \frac{b-a}{2}$, then if $y \geq \frac{(b-a)^2}{2(b-a)-(1-k)\sqrt{2(b-a)c}} + c$ there exists a pure-strategy symmetric equilibrium in which firms set prices as follows:

(i) $p_u^* = \frac{(b-a)^2}{2(b-a)-y\sqrt{2(b-a)c}}$ if all buyers are uninformed.

(ii) $p_m^{**}(k) = \frac{(b-a)^2}{2(1-k)(b-a)-y\sqrt{2(b-a)c}}$ if a fraction $k$ of the buyers are pre-search match informed.

(iii) $p_u^*(k) = \frac{(b-a)^2}{2(1-k)(b-a)-y\sqrt{2(b-a)c}}$ if a fraction $k$ of the buyers are match informed

(iv) $p_p^*(k) = \frac{(b-a)^2}{2(1-k)(b-a)-y\sqrt{2(b-a)c}}$ if a fraction $k$ of the buyers are price informed.

Moreover,

(v) In the limit as $c \to 0$, $p_u^* = p_p^* = \frac{b-a}{2}$, $p_m^* = \frac{b-a}{2+k}$ and $p_m^{**} = \frac{b-a}{2(1-k)}$.

(vi) Equilibrium price is increasing in $c$ in all four informational structures.

(vii) Equilibrium price in the different informational structures can be ranked as:

$$p_p^* \leq p_u^* \leq p_m^* \leq p_m^{**}$$

Proof: We first begin by showing that the prices given in (i) to (iv) form a symmetric equilibrium. Recalling $x'$, (i) and (ii) follow from Anderson and Renault (2000) who show that in the unique symmetric equilibrium, each firm sets its price equal to

$$p_u^* = \frac{1}{[1-F(x')]f(x') + 2\int_a^{x'} f(\varepsilon)^2 \, d\varepsilon},$$

and

$$p_m^{**} = \frac{1}{(1-k)[1-F(x')]f(x') + 2\int_a^{x'} f(\varepsilon)^2 \, d\varepsilon},$$

when all consumers are uninformed and when a proportion $k$ of consumers are informed, respectively. The functional forms in Proposition 1 are obtained after substituting for the uniform cdf and density function over $[a,b]$ in place of $F(x)$ and $f(x)$.
(iii.) We now characterize the symmetric equilibrium for the case in which half of the consumers are match informed post-search. To this effect, suppose a fraction \((1-k)\) of the consumers who first visit firm 1 learn only about the price and match value of firm 1. Let \(p^* \in [0, y - c]\) be the price that consumers expect firm 2 to charge. The difference between firm 1’s actual price and the price a consumer at firm 1 expects firm 2 to set, \(p_1 - p^*\), is denoted by \(\Delta\). The demand addressed to firm 1 by the \((1-k)\) uninformed consumers, is given by equation (9) of Anderson and Renault (2000), but we recall it here:

\[
D^U_1(p_1, p^*) = (1/2)[1 - F(x' + \Delta)][1 - F(x')] + F(x') - \int_{a-\Delta}^{x'} F(u + \Delta) f(u) du
\]

Substituting for the cdf and the density function of a uniform distribution and differentiating with respect to \(p_1\) we obtain,

\[
\frac{\partial D^U_1(p_1, p^*)}{\partial p_1} = \left[ \frac{1}{2}(1 - F(x'))f(x' + \Delta) \int_{a-\Delta}^{x'} f(u + \Delta) f(u) du \right] = \frac{-b - x + 2a}{2(b - a)^2} - \frac{\Delta}{(b - a)^2}
\]

Since by assumption \(x' > a\) and \(b > a\), it follows that

\[
\frac{\partial D^U_1(p_1, p^*)}{\partial p_1} < 0 \text{ and } \frac{\partial^2 D^U_1(p_1, p^*)}{\partial p_1^2} = \frac{-1}{(b - a)^2} < 0
\]

Hence, the demand from the uninformed consumers is downward sloping and strictly concave.

The remaining fraction \(k\) of the consumers who first visit firm 1, learn the price of firm 1 and their match values from both firm 1 and firm 2. Such consumers also expect firm 2 to set \(p^*\). The demand addressed to firm 1 by the \(k\) informed consumers consists of two parts. It partly consists of consumers who search firm 1 first. Since the decision to visit a firm is made at random, a consumer visits a given firm with probability \(1/2\). Consumers who search firm 1 first, will stop at firm 1 itself if \(\varepsilon_1 - p_1 \geq \varepsilon_2 - p^* - c\). The probability of this event is given by

\[
(1/2) \int_{a}^{b} F(\varepsilon - \Delta + c) f(\varepsilon) d\varepsilon.
\]

The remaining portion of the demand comprises of consumers who start at firm 2. Since firm 1 expects consumers who start at firm 2 to find a price of \(p^*\),
firm 1 expects that these consumers will search if $\epsilon_1 - p^* - c \geq \epsilon_2 - p^*$ and purchase if $\epsilon_1 - p_1 \geq \epsilon_2 - p^*$. Lemma 1 and equation (15) of Anderson and Renault can be used to prove that it must be the case that in equilibrium $\Delta < c$ holds. The probability that a consumer starting at firm 2 buys from firm 1 is thus given by $(1/2)\int_a^b F(\epsilon - c) f(\epsilon)d\epsilon$. The demand addressed to firm 1 by the $k$ informed consumers can therefore be written as

$$D_1^M(p_1, p^*) = (1/2)\int_a^b [F(\epsilon - \Delta + c) + F(\epsilon - c)]f(\epsilon)d\epsilon$$

Substituting for the cdf and the density function of a uniform distribution and differentiating with respect to $p_1$ we obtain,

$$\frac{\partial D_1^M(p_1, p^*)}{\partial p_1} = -\frac{1}{2}\int_a^b f(\epsilon - \Delta + c)f(\epsilon)d\epsilon = \frac{-1}{2(b-a)}.$$ 

Hence, the demand from the $k$ match informed consumers is linear and downward sloping.

The total demand addressed to firm 1 is:

$$D_1(p_1, p^*) = (1-k)D_1^U(p_1, p^*) + kD_1^M(p_1, p^*)$$

Firm 1 maximizes profit $p_1D_1(p_1, p^*)$ with respect to $p_1$. Since $D_1^U$ is decreasing and strictly concave and $D_1^M$ is decreasing and linear, and both are continuous, profit is strictly concave as a function of $p_1$ so that a unique solution to the maximization problem exists.

The first order condition is

$$D_1(p_1, p^*) + p_1 \frac{\partial D_1(p_1, p^*)}{\partial p_1} = 0$$

where

$$\frac{\partial D_1(p_1, p^*)}{\partial p_1} = (1-k)\frac{\partial D_1^U(p_1, p^*)}{\partial p_1} + k\frac{\partial D_1^M(p_1, p^*)}{\partial p_1} < 0$$

The solution $p_1(p^*)$ is obtained from the above FOC. In a symmetric pure strategy equilibrium $p_1(p^*) = p^* = p^*_{m}(k)$. Solving the latter equation, we obtain:

$$p^*_m(k) = \frac{1}{(1-k)\{[1-F(\hat{x})]f(\hat{x}) + 2\int_a^\hat{x} f(\epsilon)\epsilon \epsilon + k\int_a^b f(\epsilon - c)f(\epsilon)d\epsilon}}$$
Substituting for the uniform cdf and density function over \([a,b]\) in place of \(F(.)\) and \(f(.)\) yields the expression given in (iii).

(iv) Suppose that a fraction \(k\) of the consumers who visit firm 1 first, learn their match value from firm 1 and the prices of both firm 1 and firm 2. Suppose, without loss of generality, that \(p_1 \geq p_2\). Let \(\Delta = p_1 - p_2\). Note that for a consumer starting at firm 1, the expected benefit from searching firm 2 is \(\int_{a}^{b} (\varepsilon_2 - \varepsilon_1 + \Delta) f(\varepsilon) d\varepsilon\). The demand addressed to firm 1 by the \(k\) informed consumers consists of three parts. One, it comprises of those consumers who forego more search and purchase from the first firm they sampled. The consumer who visits first firm 1 will search firm 2 only if \(\varepsilon_1 - \Delta < x^*\). Hence a fraction \([1 - F(x^* + \Delta)]\) of consumers who visit firm 1 first, will forgo more search and purchase from firm 1. Similar analysis for firm 2 yields that a fraction \([1 - F(x^* - \Delta)]\) of the consumers who first visit firm 2 will stop there. Since the decision to visit a firm is made at random, the demand addressed to firm 1 by consumers who stop at the first firm they sample, is given by \((1/2)[(1 - F(x^* + \Delta))(1 - F(x^* - \Delta))]\). Second part of the demand addressed to firm 1 consists of those consumers who sample both firms if and only if they start at firm 2. Using the above reasoning, a fraction \(F(x^* - \Delta)\) of the consumers who start at firm 2, will search firm 1. They will purchase from firm 1 if \(\varepsilon_1 - \Delta > x^*\) i.e. with probability \([1 - F(x^* + \Delta)]\). The remaining part of the demand addressed to firm 1 corresponds to those consumers who sample both firms irrespective of where they start. Consumers who search both firms will buy from firm 1 if \(\varepsilon_1 - \Delta \leq x^*\) and \(\varepsilon_2 + \Delta \leq \varepsilon_i\). The demand addressed to firm 1 by the \(k\) informed consumers can therefore be written as

\[
D_1^p(p_1, p^*) = (1/2)[(1 - F(x^* + \Delta))(1 - F(x^* - \Delta))] + F(x^* - \Delta)[1 - F(x^* + \Delta)] + \int_{a}^{\varepsilon^* + \Delta} F(\varepsilon - \Delta) f(\varepsilon) d\varepsilon
\]

Substituting for the cdf and the density function of a uniform distribution and differentiating with respect to \(p_1\) we obtain,
\[
\frac{\partial D_1^p(p_1, p^*)}{\partial p_1} = -\frac{1}{2} [f(x^*-\Delta)] (1 - F(x^*+\Delta)) + f(x^*+\Delta)] (1 - 2F(x^*) + F(x^*-\Delta))
+ \int_{a-\Delta}^{x^*} f(u+\Delta) f(u) du \quad = \frac{-1}{b-a}
\]

Hence the demand from the \( k \) price informed consumers is downward sloping and linear.

The total demand addressed to firm 1 is:

\[
D_1(p_1, p^*) = (1-k)D_1^U(p_1, p^*) + kD_1^p(p_1, p^*)
\]

Firm 1 maximizes profit \( p_1D_1(p_1, p^*) \) with respect to \( p_1 \). Since \( D_1^U \) is decreasing and strictly concave, \( D_1^p \) is decreasing and linear, and both are continuous, profit is strictly concave as a function of \( p_1 \) so that a unique solution to the maximization problem exists. The first order condition is

\[
D_1(p_1, p^*) + p_1 \frac{\partial D_1(p_1, p^*)}{\partial p_1} = 0
\]

where

\[
\frac{\partial D_1(p_1, p^*)}{\partial p_1} = (1-k) \frac{\partial D_1^U(p_1, p^*)}{\partial p_1} + k \frac{\partial D_1^p(p_1, p^*)}{\partial p_1} < 0
\]

The solution \( p_1(p^*) \) is obtained from the above FOC. In a symmetric pure strategy equilibrium \( p_1(p^*) = p^* = p^*_p(k) \). Solving the latter equation, we obtain:

\[
p^*_p(k) = \frac{1}{(1+k)\{[1-F(x^*)]f(x^*) + 2\int_{a}^{x^*} f(\epsilon)^2 d\epsilon\}}
\]

Substituting for the uniform cdf and density function over \([a,b]\) in place of \( F(.) \) and \( f(.) \) yields the expression given in (iv).

The proof of results (v), (vi) and (vii) follows from straightforward calculations using the expressions for prices derived above and given in the statement of the proposition.

Finally, the fact that prices in every informational structure are strictly positive follows from direct inspection of their expression. It remains to show that the income constraint \( p \leq y-c \) is satisfied. From (vii), the highest of all four prices is that in the pre-search match informed case.
Thus, showing that \( p_m \leq y - c \) is sufficient to complete the proof. Re-arranging \( p_m \leq y - c \), we obtain:

\[
y \geq \frac{(b - a)^2}{(1 - k)[2(b - a) - \sqrt{2(b - a)c}]} + c,
\]

which holds by assumption. This completes the proof of Proposition 1.
Appendix B

Sample Instructions (UI – MI – PI session)

This is an experiment in the economics of market decision-making. Various research agencies have provided funds for the conduct of this research. The instructions are simple and if you follow them carefully and make good decisions you may earn a considerable amount of money that will be paid to you in cash at the end of the experiment. It is in your best interest to fully understand the instructions, so please feel free to ask any questions at any time. It is important that you do not talk and discuss your information with other participants in the room until the session is over.

All transactions in today’s experiment will be in experimental francs. These experimental francs will be converted to real US dollars at the end of the experiment at the rate of ___________ experimental francs = $1. Notice that the more experimental dollars you earn, the more US dollars you earn. What you earn depends partly on your decisions and partly on the decisions of others.

In this experiment we are going to conduct markets in which you will be a participant in a sequence of trading periods. In every period you will be a seller of a fictitious good X. The 16 participants in today’s experiment will be randomly re-matched every period into 8 markets with 2 sellers in each market. Therefore, the specific person who is the other seller in your market will change randomly after each period.

The experiment consists of 3 sections, where each section will comprise of 24 trading periods. The buyers in today’s experiment are simulated by computerized “robots”. There are 200 buyers in each of the 8 markets. Each buyer attaches a particular value to the good from each seller - which indicates how much the good is worth to the buyer. This value will be termed as “match value” in the experiment. The information available to the buyers to facilitate their purchase decisions changes in every section. Therefore, instructions pertaining to each section will be given at the start of that particular section. Furthermore, at the start of each section you will be given a starting balance of 20000 experimental francs. Any positive earnings will be added to this starting balance and any negative earnings will be subtracted from it.
Seller’s Trading Instructions

1. As a seller you can sell multiple units of good X every period but each buyer will purchase exactly one unit of the good each period. The good costs you nothing to produce.

2. At the beginning of each period, you decide on what price to charge per unit of good X. The buyers will not pay a price greater than 200 experimental francs for the single unit of good X. This maximum price is the same for all buyers and sellers and will be displayed on everyone’s decision screen. Sellers are not allowed to post a price above this maximum.

3. An example of the decision screen is shown in Picture 1. The past period pricing decisions of both sellers and your past profits and quantity sold are displayed in the lower half of the screen. You are also given information about the ‘average match value’ that all buyers would have received by purchasing good X from you and the other seller. Click Continue after making your pricing decision. The computer will wait until all sellers have made their decisions before displaying anyone’s price to the market.

Picture 1. Decision Screen
At the end of each period, your profit is computed and displayed on the outcome screen as shown in Picture 2. Your profit is calculated as follows:

\[ \text{Profit} = (\text{price} \times \text{number of units sold}) - 3500 \]

**Picture 2. Outcome Screen**

Once the outcome screen is displayed you should record all of the trading information, your price, your average match value, your quantity sold, the other seller’s price and average match value in your Personal Record sheet. Also, record your profit from this period and the total profit from all previous periods. Then click on the button on the lower right of your screen to begin the next trading period. Recall that you will be randomly re-matched with a different seller every period.

**Robot Buyers’ Match Values**

1. Each buyer receives a pair of match values in each period – the match value from seller 1 and the match value from seller 2. For each buyer, these match values are determined by computerized random draws of two numbers between 10 and 110. Each of the numbers 10.00, 10.01 …..109.99, 110 is equally likely on each draw. Moreover, these match values are independently drawn each period for each buyer. This means that the match value of a buyer does not depend on the actions of the participants of the experiments, nor on the
match values drawn for other buyers or the match values drawn in other periods. For example, if the match value of a buyer from seller 1 is 96.3 in period 1 then the match value of other buyers from seller 1 could possibly also be equal to 96.3, but they could just as easily be any other value between 10 and 110. Furthermore, each buyer’s match value is drawn independently for both the sellers. For example, if the match value of a buyer from seller 1 is 26 in period 1 then this buyer’s match value from seller 2 could possibly also be equal to 26, but it could just as easily be any other value between 10 and 110. Sellers might notice that the average match value figure displayed on the outcome screen is close to 60 in most periods. This is simply because although, as stated above, the match values are randomly drawn between 10 and 110, the number of buyers (200) is so large that the average of all match values for a seller’s product will always be a number close to 60.

2. At the beginning of each period, the buyers are randomly assigned to each seller. That is, 100 buyers start at seller 1 and 100 buyers start at seller 2. A buyer must incur a visit cost of 15 experimental francs to visit the seller and complete the purchase. However, the buyer may decide to visit the other seller prior to purchasing. If the buyer decides to visit the other seller, it can do so by paying an additional visit cost of 15 francs. This cost will remain the same throughout the experiment.

Example: Suppose a buyer is initially assigned to seller 1. It must therefore visit seller 1 first by paying a visit cost of 15.

- If the buyer decides to purchase from seller 1, then it will pay a total visit cost of 15 experimental francs.
- If the buyer decides to visit seller 2 prior to purchasing, then it will have to pay an additional visit cost of 15 francs to visit seller 2. Therefore, the total visit cost of a buyer who visits both sellers is 30 experimental francs. Note that once a buyer has visited both the sellers, it may buy from either seller.

3. A buyer’s benefit from purchasing from a particular seller is equal to

\[ 200 + \text{match value from that seller} - \text{price posted by that seller} - \text{total visit cost} \]
Section 1 (Periods 1-24)

In this section, all buyers know the price and match value of a seller only after visiting the seller. The buyer first visits the seller it was assigned to.

The buyer’s purchase decision is determined as follows:
The buyer will purchase immediately from the assigned seller if

\[
200 + \text{match value from assigned seller} - \text{price posted by assigned seller} \geq 186
\]

and otherwise it will visit the other seller.

If the buyer decides to visit the other seller, then it learns the price and match value of the other seller. It will purchase from the other seller if

\[
200 + \text{match value from the other seller} - \text{price posted by the other seller} > 200 + \text{match value from assigned seller} - \text{price posted by assigned seller}
\]

Notice that a buyer’s purchase decision depends on the match values it receives from both sellers and on the prices posted by them.

Example: Suppose a buyer is assigned to seller 1. The buyer first visits seller 1 and learns the price posted by seller 1 and its match value from the good sold by seller 1. Suppose seller 1 posted a price of 50.

- Case 1: Suppose the buyer’s match value from seller 1 is 81. Then the buyer receives $200+81-50=231$ from purchasing from seller 1. This is greater than 186, therefore, the buyer will purchase from seller 1.

- Case 2: Suppose the buyer’s match value from seller 1 is 30. Then the buyer receives $200+30-50=180$ from purchasing from seller 1 which is less than 186. The buyer will therefore visit seller 2. To do so it must pay a visit cost of 15. Upon visiting seller 2, the buyer learns the price posted by seller 2 and its match value from the good sold by seller 2.

  - Suppose seller 2 posted a price of 70 but the match value to the buyer is 61. Then the buyer receives $200+61-70=191$ from purchasing from seller 2. This is
greater than what it would receive from purchasing from seller 1 (180). The buyer will therefore purchase from seller 2.

- On the other hand, suppose seller 2 posted a price of 70 but the match value to the buyer is 22. Then the buyer receives 200+22-70=152 from purchasing from seller 2. This is less than what it would receive from purchasing from seller 1 (180). The buyer will therefore purchase from seller 1.

**Section 2 (Periods 25-48)**

In this section, there are two types of buyers.

Half of the buyers (100) are Type A buyers. They know the price and match value of a seller only after visiting the seller. Their purchase decision is made in the same manner as described in section 1.

The remaining buyers (100) are Type B buyers. Type B buyers know the price of a seller only after visiting the seller but they learn the match values of both sellers by visiting the seller they were assigned to.

Type B buyers’ purchase decision is determined as follows:

The buyer will purchase immediately from the assigned seller if

\[ 200 + \text{match value from assigned seller} - \text{price posted by assigned seller} \geq 103 + \text{match value from the other seller}. \]

If the buyer decided to visit the other seller, then it learns the price from that seller. The buyer will purchase from the other seller if

\[ 200 + \text{match value from the other seller} - \text{price posted by the other seller} > 200 + \text{match value from assigned seller} - \text{price posted by assigned seller} \]

Notice that a buyer’s purchase decision depends on both the match values it receives from both sellers and the prices posted by them.

Example: Suppose a Type B buyer is assigned to seller 1. Initially the buyer visits seller 1 and learns the price posted by seller 1 and its match value from the good sold by seller 1 and seller 2. Suppose the buyer’s match value from seller 1 is 41 and the match value from seller 2 is 60.
Case 1: Suppose seller 1 posted a price of 50. Then the buyer receives $200+41-50=191$ from purchasing from seller 1. This is greater than $103+60=163$ therefore the buyer will purchase from seller 1.

Case 2: Suppose seller 1 posted a price of 100. Then the buyer receives $200+41-100=141$ from purchasing from seller 1. This is less than $103+60=163$ therefore the buyer will visit seller 2. To do so it must pay a visit cost of 15. Upon visiting seller 2, the buyer learns the price posted by seller 2.

- Suppose the price posted by seller 2 is 32. Then the buyer receives $200+60-32=228$ from purchasing from seller 2. This is greater than what it receives from purchasing from seller 1 (141). The buyer will therefore purchase from seller 2.
- On the other hand, suppose the price posted by seller 2 is 132. Then the buyer receives $200+60-132=128$ from purchasing from seller 2. This is less than what it receives from purchasing from seller 1 (141). The buyer will therefore purchase from seller 1.

Section 3 (Periods 49-72)

In this section, there are two types of buyers. Half of the buyers (100) are Type A buyers. They know the price and match value of a seller only after visiting the seller. Their purchase decision is made in the same manner as described in section 1.

The remaining buyers (100) are Type C buyers. Type C buyers know the match value of a seller only after visiting the seller but they learn the price of both sellers by visiting the seller they were assigned to.

Type C buyers’ purchase decision is determined as follows:

The buyer will purchase immediately from the assigned seller if

$$200 + \text{match value from assigned seller} - \text{price posted by assigned seller} \geq 255 - \text{price posted by the other seller}.$$
If the buyer decides to visit the other seller, then it learns the match value from that seller. The buyer will purchase from the other seller if

\[ 200 + \text{match value from the other seller} - \text{price posted by the other seller} > 200 + \text{match value from assigned seller} - \text{price posted by assigned seller} \]

*Notice that a buyer’s purchase decision depends on the match values it receives from both sellers and on the prices posted by them.*

Example: Suppose a Type C buyer is assigned to seller 1. The buyer first visits seller 1 and learns the price posted by seller 1 and seller 2 and its match value from the good sold by seller 1. Suppose seller 1 posted a price of 50 and seller 2 posted a price of 70.

- Case 1: Suppose the buyer’s match value from seller 1 is 81. Then the buyer receives 200+81-50=231 from purchasing from seller 1. This is greater than 255-70=185 therefore the buyer will purchase from seller 1.
- Case 2: Suppose the buyer’s match value from seller 1 is 30. Then the buyer receives 200+30-50=180 from purchasing from seller 1. This is less than 255-70=185 therefore the buyer will visit seller 2. To do so it must pay a visit cost of 15. Upon visiting seller 2, the buyer learns the match value from seller 2.
  - Suppose the match value to the buyer from seller 2 is 61. Then the buyer receives 200+61-70=191 from purchasing from seller 2. This is greater than what it receives from purchasing from seller 1 (180). The buyer will therefore purchase from seller 2.
  - On the other hand, suppose the match value to the buyer from seller 2 is 22. Then the buyer receives 200+22-70=152 from purchasing from seller 2. This is less than what it receives from purchasing from seller 1 (180). The buyer will therefore purchase from seller 1.
Table 1: Search and Purchase Rules for buyer $i$

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Pre-Search Stage Information about match values</th>
<th>Optimal search rule: Which seller to search first?</th>
<th>Post-Search Stage (Information available upon searching seller 1)</th>
<th>Optimal search rule: Either buy from seller 1 or Search seller 2 if</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uninformed</td>
<td>None</td>
<td>Randomly assigned</td>
<td>$p_1, \varepsilon_1$</td>
<td>$y - p_1 + \varepsilon_1 &lt; y - p^* + x'$</td>
</tr>
<tr>
<td></td>
<td>None</td>
<td>Randomly assigned</td>
<td>$p_1, \varepsilon_1$</td>
<td>$y - p_1 + \varepsilon_1 &lt; y - p^* + x'$</td>
</tr>
<tr>
<td></td>
<td>None</td>
<td>Randomly assigned</td>
<td>$p_1, \varepsilon_1, p_2$</td>
<td>$y - p_1 + \varepsilon_1 &lt; y - p_2 + x'$</td>
</tr>
<tr>
<td></td>
<td>None</td>
<td>Randomly assigned</td>
<td>$p_1, \varepsilon_1$</td>
<td>$y - p_1 + \varepsilon_1 &lt; y - p^* + x'$</td>
</tr>
<tr>
<td></td>
<td>None</td>
<td>Randomly assigned</td>
<td>$p_1, \varepsilon_1, \varepsilon_2$</td>
<td>$y - p_1 + \varepsilon_1 &lt; y - p^* + \varepsilon_2 - c$</td>
</tr>
<tr>
<td></td>
<td>None</td>
<td>Randomly assigned</td>
<td>$p_1, \varepsilon_1$</td>
<td>$y - p_1 + \varepsilon_1 &lt; y - p^* + x'$</td>
</tr>
<tr>
<td></td>
<td>Pre-Search Match Informed</td>
<td>Search seller 1 if $\varepsilon_1 &gt; \varepsilon_2$, Search seller 2 otherwise.</td>
<td>$p_1, \varepsilon_1, \varepsilon_2$</td>
<td>$y - p_1 + \varepsilon_1 &lt; y - p^* + \varepsilon_2 - c$</td>
</tr>
</tbody>
</table>

Notes: 1. Buyers cannot purchase a good from a seller without visiting that seller.  
2. There is no outside option - the utility from “Quit” is zero. In case, buyer chooses to Quit” after searching one or both sellers, the buyer must still pay the search cost.  
3. Once the buyer visits both sellers, she obtains complete information $[p_1, p_2, \varepsilon_1, \varepsilon_2]$ and can purchase from either seller. Then, the optimal purchase rule is: Buy from seller 1 if $y - p_1 + \varepsilon_1 > y - p_2 + \varepsilon_2$, otherwise buy from seller 2. In case of a tie, the buyer can buy from either seller with equal probability.
Table 2: Experimental Design

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>4 sessions*</td>
<td></td>
<td></td>
<td></td>
<td>Content Matters</td>
<td>Timing Matters</td>
</tr>
<tr>
<td>Uninformed (UI)</td>
<td>4 sessions*</td>
<td>Price Informed (PI)</td>
<td>Price Informed (PI)</td>
<td>Uninformed (UI)</td>
<td>Match Informed (MI)</td>
</tr>
<tr>
<td>Match Informed (MI)</td>
<td>Match Informed (MI)</td>
<td>Pre-Search Match Informed (PSMI)</td>
<td>Pre-Search Match Informed (PSMI)</td>
<td>Match Informed (MI)</td>
<td></td>
</tr>
<tr>
<td>Price Informed (PI)</td>
<td>Price Informed (PI)</td>
<td>Price Informed (PI)</td>
<td>Price Informed (PI)</td>
<td>Uninformed (UI)</td>
<td>Match Informed (MI)</td>
</tr>
</tbody>
</table>

* In each robot buyer session, there are 4 duopoly markets with 200 buyers in each market.

Table 3: Theoretical Predictions and Observed Average Price

<table>
<thead>
<tr>
<th>Information Treatment</th>
<th>Equilibrium Price</th>
<th>Robot Buyer Sessions</th>
<th>Human Buyer Sessions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price Information (PI)</td>
<td>57.93</td>
<td>58</td>
<td></td>
</tr>
<tr>
<td>Uninformed (UI)</td>
<td>68.86</td>
<td>62.22</td>
<td>73.99</td>
</tr>
<tr>
<td>Match Information (MI)</td>
<td>81.56</td>
<td>73.03</td>
<td>70.60</td>
</tr>
<tr>
<td>Pre-Search Match Information (PSMI)</td>
<td>137.71</td>
<td>127.52</td>
<td>75.53</td>
</tr>
<tr>
<td>Monopoly</td>
<td>185</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Complete Information (no search cost)</td>
<td>50</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4: Mean Prices in the last 10 periods of the robot buyer sessions

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Session</th>
<th>Sequence 1</th>
<th>Sequence 2</th>
<th>Sequence 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>UI-PI-MI</td>
<td>1</td>
<td>65.50</td>
<td>54.56</td>
<td>70.58</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>66.38</td>
<td>57.98</td>
<td>73.53</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>61.40</td>
<td>55.39</td>
<td>70.41</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>66.67</td>
<td>60.24</td>
<td>69.58</td>
</tr>
<tr>
<td>UI-MI-PSMI</td>
<td>3</td>
<td>60.01</td>
<td>63.95</td>
<td>136.94</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>66.27</td>
<td>69.37</td>
<td>134.54</td>
</tr>
<tr>
<td></td>
<td>11</td>
<td>55.61</td>
<td>75.41</td>
<td>142.06</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>57.34</td>
<td>66.27</td>
<td>116.29</td>
</tr>
<tr>
<td>UI-MI-PI</td>
<td>5</td>
<td>56.25</td>
<td>65.37</td>
<td>58.49</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>57.08</td>
<td>60.89</td>
<td>58.39</td>
</tr>
<tr>
<td></td>
<td>13</td>
<td>65.52</td>
<td>64.16</td>
<td>57.31</td>
</tr>
<tr>
<td></td>
<td>14</td>
<td>58.46</td>
<td>73.74</td>
<td>61.671</td>
</tr>
<tr>
<td>UI-PSMI-MI</td>
<td>7</td>
<td>71.16</td>
<td>132.54</td>
<td>105.56</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>60.40</td>
<td>115.72</td>
<td>83.53</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>61.83</td>
<td>122.50</td>
<td>77.62</td>
</tr>
<tr>
<td></td>
<td>16</td>
<td>65.69</td>
<td>119.53</td>
<td>78.53</td>
</tr>
</tbody>
</table>

Table 5: Mean Prices in the last 10 periods of the human buyer sessions

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Session</th>
<th>UI</th>
<th>MI</th>
<th>PSMI</th>
</tr>
</thead>
<tbody>
<tr>
<td>UI-MI-PSMI</td>
<td>1</td>
<td>64.76</td>
<td>55.83</td>
<td>71.47</td>
</tr>
<tr>
<td>UI-PSMI-MI</td>
<td>2</td>
<td>73.03</td>
<td>73.61</td>
<td>73.35</td>
</tr>
<tr>
<td>UI-MI-PSMI</td>
<td>3</td>
<td>87.24</td>
<td>83.37</td>
<td>80.09</td>
</tr>
<tr>
<td>PSMI-MI-UI</td>
<td>4</td>
<td>70.94</td>
<td>69.6</td>
<td>77.22</td>
</tr>
<tr>
<td>Average Price</td>
<td></td>
<td>73.99</td>
<td>70.60</td>
<td>75.53</td>
</tr>
<tr>
<td>Equilibrium Price</td>
<td></td>
<td>68.86</td>
<td>81.56</td>
<td>137.71</td>
</tr>
<tr>
<td>Best Response Price</td>
<td></td>
<td>69</td>
<td>61</td>
<td>81</td>
</tr>
<tr>
<td>Expected price at the other seller</td>
<td>Equilibrium Price</td>
<td>Cournot price</td>
<td>Fictitious Play price</td>
<td></td>
</tr>
<tr>
<td>----------------------------------</td>
<td>------------------</td>
<td>---------------</td>
<td>----------------------</td>
<td></td>
</tr>
<tr>
<td><strong>Uninformed Treatment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Type 1 error</td>
<td>8.8</td>
<td>4.2</td>
<td>2.9</td>
<td></td>
</tr>
<tr>
<td>Type 2 error</td>
<td>14.5</td>
<td>27.6</td>
<td>25.5</td>
<td></td>
</tr>
<tr>
<td><strong>Match Informed Treatment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Type 1 error</td>
<td>2.4</td>
<td>4.6</td>
<td>3.1</td>
<td></td>
</tr>
<tr>
<td>Type 2 error</td>
<td>21.1</td>
<td>19.3</td>
<td>17.9</td>
<td></td>
</tr>
<tr>
<td><strong>Pre-Search Match Informed Treatment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Type 1 error</td>
<td>0.3</td>
<td>3.7</td>
<td>3.3</td>
<td></td>
</tr>
<tr>
<td>Type 2 error</td>
<td>31.1</td>
<td>17.5</td>
<td>16.1</td>
<td></td>
</tr>
</tbody>
</table>

Type 1 error: Subjects did not search when they should have searched, i.e., value obtained upon searching would have been higher.
Type 2 error: Subjects searched when they should not have, i.e., additional search did not yield a higher value obtained.
Table 7: Random Effects Probit of buyer $i$’s search decision

Dependent Variable: Search = 1 if buyer $i$ searched the other seller and Search = 0 if buyer $i$ purchased from the assigned seller.

<table>
<thead>
<tr>
<th></th>
<th>Last 10 periods data</th>
<th>All periods data</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Assigned Price</strong></td>
<td>0.03** (0.00)</td>
<td>0.03** (0.00)</td>
</tr>
<tr>
<td><strong>Assigned Match Value</strong></td>
<td>-0.05** (0.00)</td>
<td>-0.05** (0.00)</td>
</tr>
<tr>
<td><strong>Informed</strong></td>
<td>-0.50** (0.09)</td>
<td>-0.50** (0.09)</td>
</tr>
<tr>
<td><strong>Match = 1 if MI</strong></td>
<td>0.21** (0.08)</td>
<td>0.47** (0.13)</td>
</tr>
<tr>
<td><strong>= 0 otherwise</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>PSearch = 1 if PSMI</strong></td>
<td>-0.35** (0.08)</td>
<td>0.01 (0.12)</td>
</tr>
<tr>
<td><strong>= 0 otherwise</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Lagged Search = 1 if searched last period</strong></td>
<td>0.00 (0.09)</td>
<td>-0.07 (0.09)</td>
</tr>
<tr>
<td><strong>= 0 otherwise</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>1/ Period</strong></td>
<td>-5.84 (5.75)</td>
<td>-3.73 (4.27)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>0.65 (0.41)</td>
<td>0.06 (0.23)</td>
</tr>
<tr>
<td><strong>No of Observations</strong></td>
<td>1440</td>
<td>1440</td>
</tr>
<tr>
<td><strong>Log Likelihood</strong></td>
<td>-571.42</td>
<td>-953.70</td>
</tr>
</tbody>
</table>

Standard errors are in parentheses. ** denotes 1% level of significance and * denotes 5% level of significance.

* Probit model include subject level random effects and session level fixed effects.
Figure 1: Game tree for an 'Uninformed' buyer $i$
Figure 6: Average Posted Price in Human Buyer Sessions 1 and 3
UI - MI - PSMI

Figure 7: Average Posted Price in Human Buyer Session 2
UI - PSMI - MI
Figure 8: Average Posted Price in Human Buyer Session 4
PSMI - MI - UI

![Graph showing average posted price and equilibrium price over periods](image)

- Mean Price
- Equilibrium Price

Figure 9: Comparison of Observed and Theoretical Search Propensity

![Bar chart comparing observed and theoretical search propensity](image)

- Observed
- Cournot Expectations
- Equilibrium Expectations
- Fictitious Play Expectations

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