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An Experimental Study of the Negative Externality from Improved Information in a Differentiated Products Search Model

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This experimental study examines whether the content of information and the timing of its dissemination affects firms' market power. We construct laboratory markets that capture the key features of a price-setting, differentiated goods, duopoly model analyzed by Anderson and Renault (2000). Consumers must typically incur a search cost in order to obtain any information, but a fraction of the consumers receive partial information on price or product characteristics at no cost. The comparative statics of the model provide a ranking of prices based on whether consumers receive information on price or characteristics under different timing assumptions, generating four experimental treatments. Contrary to simple intuition, in this model the presence of informed consumers imparts a negative externality by raising equilibrium prices. The laboratory data support this negative externality prediction when sellers face a large number of automated buyers that are programmed to follow the optimal search strategy. The prices observed in the laboratory conform to the model's comparative statics and are broadly consistent with the predicted price levels. When a small number of human buyers are used, however, excessive buyer search instigates increased price competition amongst sellers. In treatments where a fraction of the consumers receive additional information, sellers post prices that are significantly lower than the treatment-specific predictions and do not correspond to the predicted ranking. This aggressive price setting behavior was found to be a rational response by the sellers to the buyer search behavior.

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I. Introduction

One of the widely accepted propositions of economic theory is that improved information leads to greater market efficiency. However, there might be instances where additional information about product attributes leads to higher prices, whereupon the informed buyers exert a negative externality on the uninformed buyers. Stiglitz states that "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, pg. 343). In this paper we use laboratory methods to investigate whether the *content* of information and the *timing* of its dissemination affect firms' market power.

The experiment captures the key features of a duopoly model with consumer search, analyzed by Anderson and Renault (2000), in which information regarding prices or characteristics of the products can be costly to obtain. Depending on the type of informational structure, the model yields different predictions. For example, sellers are able to charge a higher price when the consumers are only informed about the product characteristics as compared to the case where consumers have no information or when they have information about prices alone. Sellers are also able to charge a higher price if the information is provided to the consumer before she begins the search process. Empirical support for this type of counterintuitive prediction would be a more impressive validation of the theory than the support for the more intuitive predictions. Better knowledge of the welfare implications of different informational structures will also 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 the informational imperfection and not just its mere existence.

On one hand, theoretical search models are often quite sensitive to their assumptions regarding information acquisition and dissemination and cannot be easily adapted to accommodate industry-specific characteristics. This limits their application in actual policy prescriptions**.** On the other hand, field studies on product differentiation are limited in their ability to measure precisely consumers' valuations for different attributes. Moreover, a characteristic flaw of most empirical studies that analyze the effect of product differentiation on prices and market power is their lack of general application. Most applied competition (antitrust) studies are industry-specific and do not provide a rigorous test of the underlying theoretical models. These drawbacks provide motivation for the use of laboratory methodology. Laboratory studies circumvent the estimation problems encountered in empirical studies and the experimental inferences provide further insight into the mechanisms at work, thereby leading to a more refined theory.

In order to capture the essential features of conventional retail markets, this experiment uses the standard posted offer trading institution. We vary the number and type (human or automated) of buyers in each duopoly market. Since the focus of the paper is to examine how the content and the timing of information available to the buyers affect sellers' pricing strategy, we employ 4 different informational treatments. In the Uninformed treatment (UI), buyers do not know prior to search, either the price or their valuation (referred to as match values) of the good sold by each seller. Two other sets of treatments are compared to the baseline UI treatment. Insight on how the *content* of information affects sellers' pricing strategies is gleaned by comparing the Price Information (PI) and the Match Information (MI) treatments, wherein after all buyers have searched one of the sellers, half of them become costlessly informed about the price or their match values from the second seller. The impact of the *timing* of information is measured by comparing the Match Information (MI) treatment with the Pre-search Match Information (PSMI) treatment, in which half of the buyers know their match values from both sellers before searching either seller.

These treatments are not abstract theoretical contortions but are strongly rooted in our field environment. For most products, information about both price and product attributes is imperfect. Effective transmission of price information is often hampered when the pricing structures are complex or when the firms engage in price discrimination. Moreover, in some markets price advertising may even be illegal.[1] Similarly, arguments in favor of self-enforced bans on advertising by professionals rely on the difficulties in effectively communicating information about the type and quality of service. The UI treatment captures these market settings where the consumer must visit the seller in order to obtain any product information.[2]

The PI treatment reflects market situations where price comparisons are provided by the firm (perhaps, as an advertising device) but the consumer will still have to visit the second firm in

[1] Historic examples in the U.S. include eyeglass, liquor and prescription drugs markets.
[2] For instance, the product may be one that the consumer purchases infrequently, e.g. home improvement items.

order to ascertain the exact suitability of the product to their specific needs.[3] Even in case of online sites such as Progressive (insurance) and Travelocity (airline tickets) which provide a ‘one stop’ comparative price information, the consumer still needs to search in order to obtain an insurance coverage or travel itinerary best suited to her.

The MI treatment considers the case where during the course of a sales pitch, the consumer receives not only information about the product at that firm but also learns the product attributes at the rival firm. For instance, a real estate agent not only provides the information about their apartment complex but also how their location fares compared to the others. Similarly, a Toyota car salesman may provide information about the comparable model in Honda. The consumer must however, still visit the second firm (Honda retailer) in order to negotiate the final sales price.

Finally, the PSMI treatment captures instances where the consumers 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 consumers prior to search about their relative match values from different firms.[4] The consumer must then incur costly search in order to obtain any price information.

The theoretical model yields different price and welfare predictions for these treatments. The experimental results based on the data from eight automated buyer sessions indicate that, overall, the model predicts seller pricing behavior rather well. The comparative statics are borne out by the data and observed prices can be ranked in a manner consistent with the equilibrium. Results from 2 additional sessions with human buyers show systematic departures from theory and thereby reveals its limitations. Sub-optimal (higher) search tendencies displayed by human buyers may be the underlying rationale for the seemingly anomalous seller pricing behavior.

The paper is organized as follows: Section II examines the theoretical literature on negative externalities from improved information and the experimental literature on search models. Section III lays out the theoretical model and provides intuition for its predictions. The experimental design and procedures are outlined in Section IV and Section V describes the

[3] Retail stores like Wal-Mart routinely display “Dare to compare” prices.

[4] 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 relative low side effects of a particular drug (Tylenol versus Bayer).

theoretical predictions and testable hypotheses. Section VI contains the empirical results. Section VII concludes.

II. Literature Review

Theoretical literature

Schmalensee states "when buyers are heterogeneous, information can reduce brand specific demand elasticities by making buyers aware that some alternatives are not satisfactory" (1986, pg. 386). This captures the essence of Anderson and Renault's model that formally establishes the negative externalities from improved information. The basic underlying premise of their result is that consumers care about more than just finding the lowest price possible; they also care about their match value from the good. Wolinsky (1986) examined a costly search model where the consumers are aware of the availability of all the brands in the market but do not know either their prices or the match value from them. Anderson and Renault use Wolinsky's basic setup with a twist that some consumers are informed about the exact match value from each firm prior to search. The informed consumers reveal this information by visiting the firm for which their match value is higher. They forego further search if the price at the preferred firm exceeds the expected price by less than the search cost. This search behavior renders the firm's demand inelastic and results in higher equilibrium prices for all consumers.

The result that increased 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.[5] An intuitive explanation of why public information exerts a negative externality is that such information affects not only that agent's actions but also the actions of other agents. The effect of the latter, on the balance may be sufficiently detrimental to outweigh the direct benefit of a more informed choice.[6] Another strand of literature examines a scenario

[5] In a single agent decision problem, an expected utility maximizer always prefers more information.

[6] For example, suppose the information pertains to the high degree of substitutability of products. While the individual firm would prefer to receive the information as it does better by taking into account the higher demand elasticity and lowering its price; it will not prefer the information to be made public as it may trigger a price war. Harrington (1995) for instance, finds the value of information about demand is negative for firms selling differentiated products. Mirman et al. (1994) use this reasoning to show that for a class of duopoly games with uncertain demand, public information about the demand parameters may have a negative value; the Cournot duopolists might get closer to the collusive outcome in some states. Schlee (2001) focuses on the Pareto efficient solutions to risk-sharing problems and finds that better information makes everyone worse off if the economy has a representative agent. Some other articles that predict a negative externality from improved information include Gal-Or (1988) who examines a 'learning-by-doing' model where incomplete information about costs provides the

where information asymmetry is defined in terms of qualitatively different information structures for agents on the informed side of the market. In related works, Kessler (1996) and Levin (2001) show that market performance is in general nonmonotonic in the quality of sellers' information. Trade falls with better information if the increased buyer's curse effect operating on the demand side outweighs the potential selection effect on the supply side.

However, more pertinent to the issue at hand is this externality result in oligopolistic settings. Varian (1980) acknowledges the beneficial externality conferred by the uninformed consumers in his model of sales. He examines monopolistically competitive equilibrium price strategies in the presence of uninformed consumers. The number of stores is endogenously determined and increasing in the number of uninformed consumers. Since the informed buy at the lowest advertised price, a larger number of stores tend to lower the average price such consumers pay. Rogerson (1988) considers a model where the prices serve as a signal of quality. He shows that allowing improved information may cause the quality to deteriorate as the consumers settle for lower quality in order to obtain a more than compensating price reduction.[7] Thus, there do exist oligopolistic models of incomplete information demonstrating the disadvantages of enhanced information, but none incorporate consumer search as in Anderson and Renault.

The literature on consumer search is primarily concerned with homogeneous goods. One strikingly common feature in all search models is that the prices are increasing in the search costs. Anderson and Renault's model conforms to this universal dictum but with an additional qualification. They find that lower costs of pre-search information on product match values may actually increase prices and thereby lower consumer welfare.

Anderson and Renault build on Wolinsky (1986). In Wolinsky's model of differentiated products consumers' imperfect information reduces the substitutability among brands.[8] The basic intuition is that costly search makes it suboptimal for the consumer to examine too many substitutes and thereby limits the 'effective' substitutability. In models of product differentiation without consumer search, equilibrium prices typically rise with the degree of consumer taste for

entrant with greater incentive to produce. In a duopolistic setup, this credible threat forces reduced production by the incumbent. Hirshleifer (1971) was the first to note that public information could make the agents worse off in a contingent contracts exchange economy. Sulganik and Zilcha (1996) showed that the value of information about exchange rates could be negative for an exporting firm in the presence of future markets for currency.

[7] In an early study, Lancaster (1979) concluded that imperfect information results in softening of rivalry between adjacent firms.

[8] Wolinsky (1986) builds on previous models by Perloff and Salop (1985) and Hart (1985) that assume consumer preferences are the source of equilibrium product differentiation.

diversity. Anderson and Renault (1999) show that the picture is dramatically different in the presence of search costs. They argue that the prices should first fall and then rise with the taste for variety. Further, by introducing product heterogeneity, Anderson and Renault (1999) reconciled the "Diamond paradox" with that of Bertrand.[9] Diamond's (1971) prediction arises as the limit case of a model in which the search costs are too high or where there is product differentiation and Bertrand competition arises when the search costs and product heterogeneity go to zero.

A rather surprising feature of Anderson and Renault's result that distinguishes it from other homogeneous goods search models is the absence of price dispersion. This unique, symmetric result is in sharp contrast to models with heterogeneous search costs in which there are only asymmetrical equilibria (e.g. Salop and Stigltiz, 1977) or the models with ex ante consumer heterogeneity where there are only mixed strategy equilibria (e.g. Stahl, 1989). However, Perloff and Salop (1985) who studied a model of product differentiation similar to Anderson and Renault's rule out the existence of multiple equilibria in a duopoly market.[10] The reason primarily lies in the assumptions made in these random utility models. Caplin and Nalebuff (1991) establish that log concavity of the density function guarantees the *existence* of the price equilibrium in Perloff and Salop's (1985) model of oligopoly with differentiated products. Extending this result further, Anderson et al. (1992) prove that *uniqueness* of the price equilibrium can be ensured if the density function is differentiable. Furthermore if the costs are identical for both firms and there is some form of symmetry in preferences (both variants are equally attractive given the identical distribution assumption on match values), the random utility model is said to be exchangeable. They show that there exists unique symmetric price equilibrium for the exchangeable random utility model.[11] Therefore, the assumptions made in the

[9] Stahl (1989, 1996) also reconciled the two paradoxes by introducing heterogeneous search costs in a homogeneous commodity model.

[10] They examine multiple price equilibria in case of number of firms greater than 2.

[11] The inclusion of the independence of random variable assumption brings forth a further simplification in the equilibrium expression for prices. Note that the assumption of *i.i.d* random variables implies that observing the realization of the random variable associated with one variant conveys no information about the consumer's valuation of the other variant. The immediate consequence of this property is that variants share the market equally when they are equally priced. Even the differentiability of the density function is not required for the uniqueness result in the duopoly case. The authors include it in order to derive tractable results in a more complex model (but are not required for the purpose of our analysis).

model allow Anderson and Renault to solve for a symmetric price p^* although they initially allow for price differentiation.[12]

Experimental Literature

A majority of the existing experimental literature on spatial competition is based on voting models and considers the behavior of candidates and voters in a spatial context. However, the voting models cannot be extrapolated in the market setting since they do not have price competition. The three studies that do test Hotelling's model of product differentiation in a market setting find mixed support for the theory. Brown-Kruse et al. (1993) consider a repeated version of the spatial duopoly game with or without communication and their findings support the theoretical predictions. In the case of no communication, the results are consistent with Hotelling's model in the sense that firms tend to agglomerate at the center, while the communication treatment yields a more collusive outcome. Collins et al. (2000) use a similar setting to study a three-agent location model. As predicted by the theory, they find that firms have a strong tendency to locate at the central quartiles, though the variance of the observed choices is large. Mangani and Patelli (2001) examine a duopoly where the firms can differentiate along two horizontal dimensions. Their laboratory results, however, do not confirm the theory but resemble other experiments on prices and locations in the sense that firms tend to locate at the center. For vertically differentiated products, Holt and Sherman (1990) compared the effects of different advertising regulations in the laboratory and find that buyer surplus depends crucially on the amount of information received by the buyers.[13]

Finally, numerous experimental studies on search models have found that in the absence of public information about the prices, search costs do tend to raise the price, although monopoly prices as implied by the Diamond paradox are not consistently observed. In the first experimental study on search models, Grether, Schwartz and Wilde (1988), found the data to be largely consistent with the theoretical predictions in four of the six treatments. However, Abrams, Sefton and Yavas (2000), who examine cases predicted to have unified prices at the Bertrand and Diamond equilibria in a posted offer market with search, observe prices closer to the midpoint of

[12] The demand for each firm is one half of the aggregate demand when they charge the same price.

[13] In their experiment, buyers extracted an average of 63.8% of the trading surplus in the full-information periods. Under asymmetric information, however, buyers either lost money (in price advertising treatments) or received very little of the surplus (an average of 10.4% in treatments where consumers where ex ante only informed about the price). Other experimental studies on vertically differentiated goods include Miller and Plott (1985), Lynch et al. (1986) and Cason and Gangadharan (2001).

feasible prices rather than at either of the extremes. Davis and Holt (1996) obtain similar results. Cason and Friedman (2003) investigate the effect of noisy buyer search on price dispersion in posted offer markets. They find that the observed choices track the comparative statics predictions rather well and the support is especially strong in the automated buyer treatment. This is similar to the result by Morgan et al. (2003) who examine equilibrium price dispersion in the clearinghouse setting. The above-cited studies, however, consider only markets with homogeneous goods. In this experimental study, we extend the analysis of consumer search to differentiated products, which allows us to test a richer set of theoretical predictions.

III. Theoretical model

Anderson and Renault (2000) examine a duopoly model where each firm i sells a variant of a horizontally differentiated product. Both firms are expected profit maximizers and have identical constant cost functions, which are normalized to zero. There is a mass of consumers who have a unit demand for the good produced by either firm and have valuations that differ intrinsically across the two variants. Consumer l's indirect utility conditional on purchasing good i at price p_i is

$$u_{li}(p_i) = y - p_i + \varepsilon_{li}$$

where y is the common budget constraint and ε_{li} is consumer l's match value realization from good i. For each consumer, match values are assumed to be realizations of independent and identically distributed random variables with distribution function F which has finite support $[a,b]$. Further, the density function f is assumed to be twice continuously differentiable and log concave. Typically, the consumer must incur a search cost c in order to learn the price charged by either firm as well as his match value for the product sold by that firm. This search is without replacement and with recall. On obtaining full information, the consumer will buy the product for which their utility realization is greatest.[14]

The equilibrium solution concept considered is perfect Bayesian Nash equilibrium, where the firms maximize their expected profit given the price set by their rival and the optimal consumer search behavior. Consumers maximize expected utility taking into account the previously observed prices and match values and the expectations of the unknown price and match values.

[14] In contrast to many of the previous studies such as Perloff and Salop (1985), the authors do not include an outside alternative since no more insight can be gleaned. Instead, they assume that non-purchase will yield an arbitrarily low utility so the consumer will always purchase as long as the price does not exceed the income.

In equilibrium, price expectations are consistent with the firms' strategies and are unaffected by previously observed prices; thus, the consumers expect the firms to always charge the same price in equilibrium.[15]

Within this basic setup we examine four different informational structures: first, where all consumers are *a priori* uninformed about the prices and match values; second, where a fraction of the consumers are informed about the prices in both firms after they visit one firm but do not know the match value of the second firm; third, where a fraction of the consumers are informed about the match values in both firms after they visit one firm but do not know the exact price in the second firm and fourth, where a fraction of the consumers are informed about the realized match values in both firms prior to search. The unique symmetric equilibrium in each of these cases is summarized in the following proposition:

Proposition 1: If ε_i is uniformly distributed over the interval $[a,b]$, $i=1,2$, y is a non-binding income constraint and search cost c satisfies $0<c<\frac{b-a}{2}$, then there exists a unique symmetric equilibrium price

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

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

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

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

(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) The price is increasing in search cost c in all informational structures.

(vii) The prices in different informational structures can be ranked as follows:

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

The formal proof of the proposition appears in Appendix A. Figures A5 - A9 in Appendix A show the profit function of firm 1 when firm 2 sets the equilibrium price for each informational

[15] Thus, even when the consumer observes a price different from the equilibrium price on sampling the first firm, the optimal search rule does not change. She continues to expect the other firm to charge the equilibrium price.

structure. The functions are single peaked and attain a unique maximum at the symmetric equilibrium price.

The model with completely uninformed consumers is essentially Wolinsky's (1986) model in the duopoly setup. Following a similar convention, Anderson and Renault begin by deriving the demand facing each firm in a symmetric configuration. To do so, they first characterize the decision problem of the consumer who expects both firms to charge the same price p^* and who can gather information at the cost c per observation. This allows them to uniquely define a critical x' such that the consumer with match value x' is indifferent between staying at the first firm he sampled and searching the other firm. Thus x' is defined by the following equation

$$\int_{x'}^{b} (\varepsilon - x') f(r) dr = c \qquad (1)$$

We consider the case where the critical value x' is greater than the lower bound of the match valuation distribution, a.[16] The expected demand for the firm can then be stated as a function of its own price p and the price of the other firm p^* (or more concisely, as a function of the price premium p-p^*). Each firm maximizes its profit by setting its price equal to the unique and symmetric p^*.

It is important to note that product heterogeneity provides a "search model with search" i.e., in equilibrium, the consumers search with a positive probability. In the Diamond model, there is no search in the equilibrium since the consumers rationally expect all firms to charge the monopoly price. Although consumers price expectations are exactly satisfied in this model, adding product heterogeneity means that even the consumer who finds the expected price may continue to search for a better match. This brings the firms in direct competition with each other and helps resolve the Diamond Paradox.

The most striking feature of the equilibrium comparative statics is that they are in sharp contrast to the usual economic reasoning of the positive externality imparted by the informed consumers. First, informational content matters. While price information lowers the equilibrium price, match information irrespective of the time of its provision increases the equilibrium price. The match-informed consumers search less than the price-informed or the uninformed

[16] No consumer will search if $x' < a - (p-p^*)$, where p-p^* is the premium charged by the firm. Similarly if $x' < a$ the consumers will search only if they anticipate a large enough price difference. These cases symbolize the Diamond Paradox in the sense that the only NE for all firms is to price at the budget constraint. At any price lower than y, the firms can raise price (and profit) without losing any customer. The $x' > a$ condition can be obtained by putting a restriction on the maximum possible value of search cost.

consumers, making the demand more inelastic and granting the firms additional monopoly power. Second, the timing of information dissemination matters. While lower search cost c will still increase consumer welfare, here, it is the lower cost of presearch information that actually decreases consumer welfare. If all the consumers are informed about match value prior to search, the firms charge the maximum price that the consumers can afford, y.

Aside from this distinction, the other comparative statics of the model are intuitive and are similar as elsewhere in the literature. For instance, note that similar to Salop and Stiglitz's (1977) model, the prices are increasing in search costs. As the search costs increase, the consumers are less inclined to search and this bestows more market power to the firms who raise their prices. The consumers thus suffer from both the direct effect of being unable to get a better (possible) match and the indirect effect of higher prices. In this paper, we do not study the impact of higher search cost on prices, but focus on the effect of the content of consumers' information and the timing of its dissemination.

The model is intuitive and yields stark predictions. It would be useful to test its empirical validity in the laboratory where the data are not plagued by the confounding factors that bias the field data. Laboratory control allows direct test of causal predictions on the small scale and thereby provides guidance for future theoretical work that can more realistically capture features such as bounded rationality of the consumers (or even firms).

IV. Experimental Design and Procedures

In this laboratory study, four informational structures and two types of buyer population are considered. In the baseline UI treatment all buyers are *a priori* uninformed about product attributes while in the three other comparison treatments, the proportion of informed buyers is exogenously set at 0.5. The buyer treatment varies the number of buyers per seller and the buyer search strategies. Table 1 summarizes the experimental design, detailing the sequence order of different informational treatments.

Each experimental session consists of three sequences of twenty four periods each. The first sequence always constitutes of the baseline UI treatment. Since the focus of this study is the impact of different informational conditions on sellers' pricing strategy, we include two other informational treatments in each session. Having the same set of subjects make decisions under three different treatments has the advantage of directly controlling for subject variability. It enables the effect of change in information 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 information treatments helps measure and control for these experience effects.[17] For instance, in Session 1, the "UI- PI- MI" session, the first sequence of twenty-four periods considers the treatment where buyers are *a priori* uninformed about both the price and match value and must visit a seller in order to obtain this information. In the next sequence, half the buyers receive price and match value information of only the seller they visited, while the remaining half are also informed about the price of the second seller. In the last sequence, after all buyers visit one seller, information imparted to half of them also includes the information about their match value from the second seller. The ordering of the last two sequences is reversed in Session 3 (UI- MI-PI). A similar design pattern is also used for sessions including the PSMI treatment.

As discussed earlier, previous experimental studies have focused on homogeneous products, where buyers do not search in equilibrium. In case of differentiated products however, while there is still no gain from searching for a better price, in equilibrium buyers do search for a better match value. In fact, in keeping with much of the search literature, price expectations are assumed to remain unaffected by the repeated observation of non-equilibrium prices and the equilibrium search decision is based on the expected match values alone. These assumptions, however, may not hold in practice. Prices are equal in equilibrium, but disequilibrium play is likely to be common both in the lab and in the field. Moreover, buyers are boundedly rational, and as noted by Cason and Friedman "human buyers might not follow strictly a reservation price strategy, much less (an) identical reservation strategy" (2003, pg. 239). Differing buyer behavior may then influence sellers' pricing strategy. For instance, if search costs are low, the human buyers may decide to search a seller who they know yields a (slightly) lower match value, in the hope of obtaining a much lower price quote and therefore a higher overall benefit. This in turn provides the sellers an incentive to engage in price competition. The process therefore perpetuates itself: Differing seller experience encourages differing pricing behavior, which in turn encourages differing search strategies by the buyer.

[17] This is not an explicit test for separability. Kagel and Levin (1986) however, argue that such a concern is unwarranted. They reason that in analyzing these single shot games we are implicitly assuming that the utility function is intertemporally separable in profits.

By varying the number and type (human versus automated) of buyers we provide both the test of the theory as well as outline its boundaries. The model calls for a continuum of buyers. In the experimental setting, this can be approximated by simulating the buyers with computer algorithms (or robots). The treatment in which large numbers of robot buyers play a known equilibrium strategy eliminates the extraneous variability arising from sample variance and buyer idiosyncrasies. This allows the focus to be centered entirely on seller behavior that is central to the theory. Evidence of the model's empirical value is obtained by analyzing sellers' pricing strategy when confronted with a finite number of human buyers, as in naturally occurring markets in the field.

Experimental Procedures

This study reports results from 8 sessions with automated buyers and 2 sessions with human buyers. All 10 sessions were conducted in the Vernon Smith Experimental Economics Laboratory at Purdue University. Subjects were recruited from introductory undergraduate economics classes. Most subjects were experienced in the sense that they had participated in a market experiment before, although they were unfamiliar with this exact trading environment. No one participated in more than one session reported here. A computerized interface using the software z-Tree was used to implement the experimental environment (Fischbacher, 1999). General trading instructions were read aloud at the beginning of the experiment. New instructions pertaining to the relevant informational treatment were read at the beginning of each sequence. Throughout the sessions, no communication between subjects was permitted and all choices and information were transmitted via computer terminals.

At the beginning of each run of 24 periods, the subjects received a starting balance of approximately $1.[18] All transactions in the experiment were in terms of francs, which were converted to real dollars at the end of the experiment using a known and common conversion rate. The exchange rate was calculated such that subjects' earnings would average approximately $25 for sessions lasting 120 minutes.[19] In the experiments, earnings ranged from $20 to $32.

The experiment was instituted as a duopoly Posted Offer market and proceeded as follows: In the robot buyer treatment, all subjects were assigned the role of a seller. The 16 participants in

[18] This starting balance was provided in order to avoid bankruptcy which might be an issue in the earlier periods while subjects are still learning the incentives of the game.
[19] Given the chosen parameters, conversion rate was different for the PI and PSMI sessions.

each experimental session were divided into 2 independent groups and in each period, sellers were randomly re-matched into new pairs to form eight duopoly markets. This random re-matching took place within each independent group so that we obtained 2 statistically independent observations from each session. In the human buyer treatment, 18 subjects in each session were divided to form 3 duopoly markets with 4 buyers in each market. The subjects were initially randomly assigned the role of either a buyer or a seller and their role remain unchanged for the entire length of the experiment.[20] In the human buyer treatment 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. We chose to regroup subjects each period in order to minimize the repeated game incentives such as reputation formation and collusion.

The sellers had zero production costs and no capacity constraints. Buyer search cost was kept constant at 15 in all sessions. Consumers 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.[21]

In each period a 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,…,110}. Therefore, match values were exogenous, were not a choice variable of either the seller or buyer. Unlike other experiments on differentiated products where demand is exogenously specified to be a function of own and other seller price, in our experiment the demand takes into account the degree of differentiation. This means that even if both sellers charge the same price, if buyers engage in optimal search then demand is greater for the seller for whom a larger proportion of buyers receive a higher match value.[22] This information was provided in the instructions and is therefore assumed to be common knowledge. It was also made clear to the subjects that the match values of a buyer do not depend on the actions of the

[20] This should promote learning, since subjects will not need to adjust to the changing market roles.

[21] The income constraint was imposed because Anderson and Renault (2002) find that providing consumers with match information might precipitate a holdup problem causing the market to cease to exist. Consider a consumer who knows the exact match value and visits the firm expecting a price p. It then follows that his match value must be at least $p + c$. Since the search cost is sunk, the firm can effectively raise the price up to $p + c$ without losing the consumer. The consumer anticipates this holdup problem and will refuse to incur search and the market will cease to exist. With a maximum willingness to pay, even at the highest possible price, the consumer will receive a utility equal to his match value and will therefore always buy, thus solving the existence problem.

[22] In theory, match values are symmetrically distributed across the two sellers. The random choice of match values in the experiment, however, might allow for a higher average match value from a particular seller in a given period.

participants in the experiment, nor on the match values drawn by other buyers or the match values drawn in other periods.

The trading in the market proceeded as follows: Each seller posted a single price every period. The buyers were randomly assigned to a seller every period and upon paying the visit cost, received the product (price and match value) information of the assigned seller. Depending on the informational treatment, half of the buyers also received price or match value information of the second seller. Every period, this information was equally likely to be shown to each buyer and the z-Tree software running the experiment randomly determined which buyer actually received the information.

After both sellers made their pricing decision and the relevant information, if any, was conveyed to some of the buyers, all buyers made their costly search decision. The automated buyers were programmed to follow an optimal reservation value strategy with the following characteristics. In the UI treatment, buyers receive information from only the assigned seller. In their decision to search again, we assume that buyers expect the second seller to set the equilibrium price and search is based only on the difference between the observed and expected match value. In the PI treatment, the search decision is based on both the known price premium and the expected difference in match value while in the MI treatment, the search decision is based on the known difference in match values and the expected price premium. The informed buyers of the PSMI treatment always chose to first search the seller with the higher match. In all treatments, the optimal search strategy simply entails that buyers will visit the second seller only if the 'price-match' value combination from the first firm is less than the (exogenously-determined) equilibrium reservation value. This reservation value strategy which determines the buyers' search decision was revealed to all the sellers in case of automated buyer treatment. Of course, in the human buyer treatment buyers' search and purchase decisions may not correspond to these equilibrium rules. Detailed examples were provided to illustrate the different scenarios and highlight differences across treatments. Instructions are attached as Appendix B.

At the end of the trading period, profits for all agents in the market were reported.[23] In addition, the sellers' result screen listed information about the average match value received by

[23] The seller profit in the automated buyer treatment was Revenue – Fixed cost (3500 experimental francs). The use of fixed cost is not uncommon in search experiments (e.g. Sonnemans, 1998). It is introduced in order to make the payoff function steeper around the equilibrium and thereby make the incentives for adopting the equilibrium strategy

the buyers initially assigned to him and to the paired seller, as well as the price posted by the paired seller. The buyers were informed about the match value received, and the price and search cost paid. At the beginning of the next trading period, sellers were provided a history table detailing the average match values, past prices and profits in their market. [24]

V. Theoretical Predictions and Testable Hypotheses

The equilibrium derived in Anderson and Renault and our calculations are used to compute the theoretical predictions shown in Table 2. Figure 1 sketches the equilibrium price levels for all informational treatments across differing levels of search cost.

We test a set of six hypotheses. Hypothesis 3A is the only purely quantitative hypothesis, but hypothesis 1A can also be viewed as a somewhat flexible test of the equilibrium point predictions. The last two hypotheses pertain to the behavioral implications resulting from allowing non-optimal buyer search strategies. The remaining hypotheses are a test of the model's comparative statics predictions.

Hypothesis 1A: Price variance declines over time as prices converge to the treatment-specific equilibrium price shown in Table 2.

Hypothesis 1B: In all treatments, the market price is bounded away from the monopoly price.

Unlike in a homogeneous goods environment, where presence of differentially informed buyers yields price dispersion as the equilibrium outcome, in our differentiated goods setting there is a unique market price (Table 2). Moreover, in all treatments the market price is bounded away from the monopoly price (147.5) because in equilibrium, buyers may search for a better match value.[25]

Hypothesis 2: The price in the Price Information treatment is lower than the price in any other informational treatment, in which buyers do not know the prices. (Content matters)

Simple economic intuition tells us that more information about prices increases the sellers' incentive to engage in price competition in order to capture a higher proportion of demand,

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more salient. Given the finite number of buyers in the human buyer treatment, this incentive enhancement mechanism was 'wrongly' deemed to be unnecessary.

[24] This trading information about the rival duopolists helps generate more informed and perhaps common expectations and therefore may result in faster convergence to the equilibrium.

[25] Derivation of Monopoly price is contained in Appendix A.

thereby exerting a downward pressure on the equilibrium price. This holds true even when goods are differentiated as is evident in the formal theoretical model.

Hypothesis 3A: In the Pre-search Match Information treatment, the price is twice as high as in the No-information treatment.

Hypothesis 3B: Prices are higher with pre-search match information than without any information. (Timing matters)

Given that the sellers are symmetric and buyers always buy, in all treatments the expected demand faced by each seller is half of the aggregate demand. However, in case of pre-search match informed buyers, only the proportion of the demand addressed by uninformed buyers is price sensitive. This implies that in equilibrium the elasticity of a seller's expected demand is reduced by exactly that proportion, thereby increasing the price accordingly.

Hypothesis 4: The price in the Match Information treatment is higher than the price in the Uninformed treatment (Content matters) but lower than the price in the Pre-search Match Information treatment (Timing matters).

This qualitative hypothesis underlines the impact of both timing and content of information on the market outcome. In general, providing match information curtails the propensity to search again since the search decision is based on known difference in match values and the assumption that the other seller always sets the equilibrium price. By providing this information prior to search, a seller can further reduce the demand elasticity for her product and exploit increased market power.

Hypothesis 5: The automated buyer treatment will have faster convergence to the equilibrium price.

As discussed earlier, both finite number and differing human behavior open the possibility of strategic manipulation by the either agents and this may delay, or possibly even prevent, the convergence to the equilibrium. Sellers setting the same price may nevertheless be sampled by different number of buyers in different periods and consequently earn different profits. By having computer simulated buyers that always follow the equilibrium strategy, we can reduce sample variability and thereby facilitate faster learning and convergence to equilibrium.

Hypothesis 6: Buyers search according to the treatment-specific optimal search rule.

Depending on the informational treatment, optimal search rule is calculated using the known or the expected price premium and difference in match values. The actual search decisions made by human buyers can be compared to this optimal search strategy.

VI. Statistical Methods and Results

The experiment provides a rich panel dataset of pricing decisions under different informational treatments for a time series of 72 periods across 10 sessions and 68 markets. Figures 2-5 and 10-11 display the time series of average prices in the automated and human buyer treatment respectively. Given the obvious difference in results of the two buyer treatments, we split our analysis accordingly. Section VI.A examines the sellers' pricing behavior when (automated) buyers follow the optimal risk neutral search strategy. The focus is primarily on testing the model's comparative statics predictions and on the quantitative comparison of the observed and equilibrium price. Section VI.B includes a similar analysis for prices in markets where sellers face human buyers who may or may not engage in optimal search. We also examine the buyer search behavior in order to explain the anomalous result between the two buyer treatments. Section VI.C contains a brief discussion on the comparison between the human and robot buyer treatments.

VI.A Automated Buyer Treatment

The fact that prices in each session move in accordance to the directional prediction of the model is evident from Figures 2-5. Although there are significant treatment switchover effects and price variance does not decline even in later periods, overall the prices exhibit the predicted pattern and appear to conform to the model's comparative static predictions.

Note that our design varied both the nature and the sequencing of the treatments in the three runs of each session. In addition to within-session comparison, this allows us to investigate whether the prices for the same informational treatment differed across different sessions and sequence orderings. Figures 6-9 display the time series of prices in a given treatment for different experimental sessions. While the comparative statics effects are always observed, quantitative comparisons yield mixed results and indicate marked differences across treatments. In all cases except the MI treatment, there is a definite time trend: prices in the initial periods of a run are above (UI and PI) or below (PSMI) the equilibrium prediction but later tend towards the prediction. In the later periods, the UI and PSMI prices are unilaterally lower compared to the equilibrium prediction while the MI and PI prices display varying rates of convergence to the equilibrium. Formal statistical analysis discussed below, provides a more rigorous support to the visual impression gleaned from the graphs.

VI.A.1 Comparative statics

Table 3 presents the mean prices in the last 10 periods of all three runs of the robot buyer sessions. As noted earlier, random re-matching of sellers to markets is an important part of our design, since it minimizes the repeated game incentives. Moreover, the theoretical framework for the experiment is based on static, one-shot games. The cost of this design choice is that it limits the number of statistically independent observations generated by each group of subjects. For data analysis, we therefore use the conventional nonparametric tests which do not require many statistical assumptions and still apply to small sample sizes obtained from the sessions.[26] We use the Mann-Whitney test for across-session comparisons and the Wilcoxon Signed Ranks test for within-session comparisons. Each automated buyer session has two independent groups, so we have 16 independent observations for the UI and MI treatments and 8 independent observations for the remaining two treatments.

The Wilcoxon Sign Rank test rejects the null hypothesis that within the same session, 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 = 0.0005). A similar comparison of prices in the MI treatment with the PI and PSMI treatment prices produce signs that are all in favor of the directional alternative predicted by the model.[27] The sole exception to this finding is the comparison of UI and PI prices (p-value = 0.09). This discrepancy may partly be explained by the ordering of the sequences. The mean price in the UI treatment always exceeds that of the PI treatment when PI treatment immediately follows the UI treatment in sequence 2. However, in 3 out of 4 cases where PI is the last sequence (preceded by

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[26] Generating many independent observations for a market like this is not feasible for any reasonable experimental budget, especially since our goal is to test a static theory in an environment where learning is possible. The absence of auxiliary parametric assumptions also makes the use of nonparametric methods attractive. For e.g. a *t*-test of the equality of two sample means is based on the assumption that the observations are independent draws from normal distributions.

[27] In fact, all of the 8 pairwise differences favor the theoretical prediction (p-value = 0.012). The results are the same when sign test was employed for these within-session comparisons.

a higher-priced MI treatment), the mean price in the PI treatment exceeds that of the UI treatment.

Independent across-session comparison of prices in different treatments also finds support for comparative static prediction of the model.[28] Results indicate that prices are significantly different in all treatments at better than the 5% significance level. In fact unlike the within-session comparison, Mann-Whitney test yields that even the UI-PI equality can be rejected at a 10% level of significance (one tailed p-value=0.059, n=m=8).

The Mann-Whitney test was also employed to analyze the impact of sequencing order on the subjects' decisions. Unlike PI and PSMI treatment, the 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, (Figure 8). On the other hand, when either UI or PI treatment preceded the MI treatment, the prices are always below the prediction. Further, MI prices are always higher when it is the last treatment sequence in a session, so as expected, 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). The non-parametric tests for profit yield similar results.

In addition to nonparametric methods, we can make statistical inferences by using the panel data econometric methods that model the dependence of observations (and errors) due to the repeated measures drawn from the same set of subjects. These include random effects models for subject-level price choices and fixed effect models for session-level analysis of treatment ordering. The estimates are corrected for heteroscedasticity and possible spatial correlation. In order to control for possible time trend, we include 1/period. Prices are widely dispersed in the initial periods of any run since the subjects are still trying to grasp the basic incentives involved. In order to account for the treatment switchover effect documented earlier and any possible learning and hysteresis effect, we restrict our analysis to the data from the last 10 periods of each run.[29] For a given informational treatment *a*, subject level random effect regression equation is

$$p_{i,t} = \alpha + \beta_1 D_t^b + \beta_2 D_t^c + \beta_3 D_t^d + \beta_4 (1/t) + \delta d_t + \lambda s_t + \varepsilon_{i,t} \qquad (1)$$

[28] For example, we employ the Mann-Whitney test to compare PI prices from sessions 1, 3, 5 and 7 to MI prices from the remaining sessions 2, 4, 6 and 8.

[29] Since subject behavior stabilizes considerably after the first few periods, results from the analysis of the last 10 periods are no different from the analysis of the last 5 periods.

$p_{i,t}$ 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_t is a vector of session dummies

s_t is a vector of sequence dummies

$\varepsilon_{i,t}$ is the composite error term.

The coefficients on the treatment dummies indicate whether prices differed in those treatment compared to treatment *a.* The regression results show that all treatment dummies are significant and have the predicted sign. Therefore, 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. Despite concentrating on the last 10 periods of each treatment run, we find the time trend to be significant (p-value =0.02) indicating that learning is an ongoing process. The sequence dummy is also found to be significant, consistent with the non-parametric results discussed above.

Finally, note that some session effects were significant. This indicates that even after accounting for random subject effects and sequencing-order effects on subjects' pricing decisions, the full extent of across session variability is not captured. The baseline treatment allows us the isolate the variability attributable to the sessions alone, without the confounding effects introduced by the sequence ordering. The UI treatment is always the first treatment in every session and as can be seen in Table 3, the mean UI prices ranges from 55.61 to 71.16.

In conclusion, based on both parametric and nonparametric methodology, the prices and profits can be empirically ranked as follows:

$$PI \leq UI < MI < PSMI$$

This ranking provides definite support for hypothesis 3B and hypothesis 4. Prices are significantly higher in the treatment where buyers are provided match information of the second seller than in treatments in which either no information or just price information was provided. Prices are also higher when match information is provided prior to any search (PSMI) rather than after the first search (MI). Hypothesis 3A, which quantifies the PSMI price as twice the UI price also finds strong support in the laboratory. The ranking also implies that we cannot reject Hypothesis 2. Prices are lower when subjects receive information about price of the second seller than if no information or match information was provided. Therefore, the observed ranking supports all comparative statics hypotheses and conclusively shows that both the content of information and the timing of its dissemination matter for price formation in search markets with differentiated goods.

VI.A.2 Equilibrium quantitative comparison

Recall that the primary focus of our study is to compare the equilibrium price predictions across different informational treatments. Evaluating the predictive power of the model should not consist of qualitative rankings alone. Therefore, we now turn to a more demanding test of the theory. By comparing the observed prices to their equilibrium values, we are able to assess how well the model can predict pricing behavior observed in the laboratory. The panel data regression equation used for this comparison can be stated as follows

$$p_{i,t}^{a} - p^{a*} = \alpha + \beta(1/t) + \delta d_t + \lambda s_t + \varepsilon_{i,t} \qquad (2)$$

where
- $p_{i,t}^{a} - p^{a*}$ is the difference between the subject i's price in period t and the equilibrium prediction for treatment a
- d_t is a vector of session dummies
- s_t is a vector of sequence dummies
- $\varepsilon_{i,t}$ is the composite error term.

Regression results indicate that MI prices in the last 10 periods are significantly lower than the predicted levels (p-value=0.02) but the prices in the other three treatments are not different from their treatment-specific equilibrium prediction.[30,31] Hypothesis 1B also finds strong support from the data suggesting that product differentiation provides enough incentives for sellers to act more competitively than they would in a similar search environment with homogeneous goods.

For complete assessment of the model, in addition to testing the point predictions, we must also 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

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[30] The time trend for the PSMI treatment is negative and significant at the 1% level indicating that prices increase over time. This is consistent with the visual impression shown in Figure 7. The time trend is not significant in the other three treatments.

[31] A similar comparison of the observed and predicted profit yields a slightly different result. We find that the observed UI profits are significantly lower than predicted levels (p-value = 0.01), while they are consistent with the model's prediction in the other three treatments.

$$v_{it} = \sum_{i=1}^{j} D_i \left(\beta_{ot} \frac{1}{t} + \beta_{ft} \frac{t-1}{t} \right) + u_{it} \quad (3)$$

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, β_{ot} reflects the predicted variance at the beginning of the treatment run and β_{ft} indicates the predicted asymptote in the final period.

Hypothesis 1A receives mixed support from the data. Price dispersion remains significantly positive even asymptotically. However, for all sessions β_{ft} term is closer to zero than the corresponding β_{ot} term indicating a clear decline in 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 at less than 1% level. Equality of the initial and final variance asymptote is rejected in 5 out of 8 sessions of the PI and PSMI treatments. In this context two points need to be noted: One, β_{ot} and β_{ft} terms differ significantly across (some) sessions of the same informational treatment, indicating session heterogeneity. Two, decline in variance tapers off. When we restrict the analysis to the last 10 periods (i.e. starting period is period 16), then across all 16 sessions the $\beta_{ot} = \beta_{ft}$ equality is rejected only 4 and 5 times in the UI and MI treatment respectively. The proportion remains unchanged for PI and PSMI treatments.

The following summarizes the results from the automated buyer treatment:

Result 1: Comparative statics predictions of the model hold. The prices and profits can be empirically ranked as PI ≤ 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 the prediction. Variance of prices declines over time but does not converge to zero.

VI.B Human Buyer Treatment

The results with robot buyers provide nearly uniformly positive support for the theoretical model. However, the model's prediction may not be supported when the pre-programmed and observable buyer strategies are replaced with human buyers who may now follow a reservation price strategy, and may search suboptimally.

Table 4 and Figures 10 and 11 orient the discussion in this section. The figures display the time series of mean prices and their variance in the two human buyer sessions and the table provides the mean price in the last 10 periods of all three informational treatment sequences. From the figures, it is clearly evident that prices in MI and PSMI treatment are low and show no sign of convergence to the predicted levels. Prices in the UI treatment, on the other hand, start high but tend towards the equilibrium prediction in the later periods. The summary statistics in the Table 4 not only indicate the level of divergence from the equilibrium but also reject the comparative statics predictions of the model. (The best response price is discussed later).

To assess the statistical significance of these results, we use the parametric methods described in the previous section (equations 1-3). 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.[32]

The regression results show that while prices (and profits) in all three informational treatments are significantly different, they do not conform to the model's comparative statics prediction. More precisely, the price in the MI treatment is significantly lower than the price in the UI treatment (p-value= 0.01); and while the PSMI price is higher than the UI price as predicted (p-value=0.3) the value of the coefficient does not reflect the predicted level of difference. The price and profits can therefore be ranked as follows:

$$MI < UI < PSMI$$

Equilibrium quantitative comparison yields that while the observed prices in the last 10 periods of the UI treatment are not significantly different from the equilibrium prediction, prices (and profits) in the other two treatments are significantly lower than the treatment-specific prediction (p-value = 0.00).[33] Furthermore, the variance of posted prices declines over time but does not converge to zero (except for one session of UI treatment). Analogous to the automated

[32] 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. Also, since the sequence ordering of treatments is unique in each human buyer session, session fixed effects subsume sequence effects. Additional human buyer sessions are planned for fall 2005.

[33] Only in case of MI treatment is the trend variable significant, consistent with the downward tending price line observed in Figures 10 and 11.

buyer session, the decline in variance tapers off; i.e., subject behavior is relatively stable when we consider only the last 10 periods.

Before concluding the failure of the model to accurately predict the market outcome, we need to ascertain the reason for the observed deviation from equilibrium outcome. It is possible that the sellers' suboptimal pricing behavior observed in the lab is actually a best response to the buyers' search strategy. Therefore, in the next subsection we detail buyers' search decisions and examine its impact on sellers' pricing decisions.

VI.B.1 Buyer search behavior and Seller pricing decisions

Theory predicts that although the buyers' price expectations are satisfied in equilibrium, they continue to search for a product with a greater match value. Providing match value information before or after the first search reduces this search propensity. When the buyers are *a priori* informed about their match valuations from both sellers, expecting both sellers to set the same price, they search only the seller for whom their match value is higher. When they are informed about the match value from the second seller after visiting the first seller, then the additional search is conducted only if the known difference in the match values and expected price premium exceeds the cost of search. We define search to be 'optimal' if the value obtained from the (assigned) first seller is less than the equilibrium reservation value obtained from searching the second seller.[34] In theory, since match values are assumed to be uniformly distributed across the two sellers and both set the same unique equilibrium price, the informed consumers should not search at all. In the experiment, however, the randomly chosen match values are not always symmetrically distributed and the sellers rarely set the same price, so it might be optimal for the informed sellers to conduct additional search.

Figure 12 compares the theoretical search propensity distribution with the one estimated using the data of the last 10 periods.[35] It is evident that while the empirical search distribution in

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[34] It must be noted, however, that the incentives for search differ for the informed and uninformed buyer. While the uninformed buyers are assumed to use the reservation match value, the informed buyers choose to search based on the actual match value from the second seller.
For uninformed buyers: Equilibrium reservation match value from additional search = Income (200) + reservation match value (55.23) – treatment-specific price prediction – search cost (30)
For informed buyers: Equilibrium reservation match value from additional search = Income (200) + match value from the second seller – treatment-specific price prediction – search cost (30)

[35] We trace out search probabilities for different price levels using probit regression estimates that use value obtained from both sellers and time trend as explanatory variables for the buyer search decision.

the UI treatment is the mean preserving spread of the theoretical distribution, the other two treatments shows substantial and systematic deviation from the predicted search behavior. Table 5 provides frequency statistics of the optimal and observed search behavior in different informational treatments. When all the buyers are uninformed, 38.72% of the times optimal behavior involves searching the second seller. In the presence of post-search match informed buyers the overall optimal search propensity is lower at 24.31% and in the PSMI treatment, equilibrium price is so high that additional search is optimal for a miniscule 0.52% of the (uninformed) buyers.

Table 5 also details the observed search behavior. While the search propensity in the UI treatment is not very different from the optimal search, the search propensity in the other two treatments is at least twice the predicted level. Contrary to the model's prediction, more subjects chose to conduct additional search in the MI treatment (52.92%) than in the UI treatment (45.66%). In fact, in the MI treatment the informed consumers searched the second seller more often than did the uninformed consumers.[36]

Note that the observed non-optimality in search behavior may be subdivided into two types of error.

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

Type 2 error: Subjects searched when they should not have i.e. the additional search did not yield a higher 'value obtained'.[37]

From Table 6 it is evident that subjects in the MI and PSMI treatment more often erred on the side of 'unnecessary' search (Type 2 error). Further, while the difference between informed and uninformed buyers is not stark for the MI treatment, the uninformed buyers in the PSMI treatment were more likely to conduct additional non-optimal search.

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[36] For the MI treatment, the correlation between additional search and information is significant at 1% level for all periods and at 10% level for the last 10 periods. In case of the PSMI treatment on the other hand, 78.87% of the uninformed buyers searched the second seller as compared to 21.13% of the informed buyers.

[37] The optimal search comparisons presented here define optimality in terms of the equilibrium reservation price strategy. Optimality may also be defined by taking into account the actual match values and price levels of both sellers, i.e. the value obtained from the (assigned) first seller is compared to the *actual* value obtained from the second seller. This "comparative" search comparison yields that a higher fraction of the uninformed buyers committed Type 1 error (missed search opportunities) in both MI and PSMI treatment (15.6% and 8.9% respectively). Apart from that the difference between the "comparative" and "optimal" search comparisons is relatively minor.

Seller pricing decisions

The increased buyer search documented in almost all informational treatments results in a more transparent and informed environment where the sellers have an incentive to engage in price competition. The observation that prices are lowest in the treatment where the search propensity is highest supports our claim. More precisely, the higher search propensity observed in the MI treatment as compared to the UI treatment might therefore explain the anomalous result that the prices in the MI treatment are less than in the UI treatment. Similarly, while the search propensity in the PSMI treatment is the lowest (29.58%) - yielding the maximum observed price- the large difference between the observed and optimal search behavior explains the large deviation between the observed and equilibrium price outcome.

The next question is whether these low prices are actually the sellers' best response given the buyer search behavior. To analyze this, we begin by calibrating the probabilistic buyer search rule for each informational treatment. We use the probit search regressions where the price and match value are used as explanatory variables for the buyer search decision.[38] The regression estimates enable us to trace out the search probabilities for different levels of observed prices. The approximate "probabilistic" demand curve facing (assigned) seller *a* when she sets price p_a, is then calculated using the following equation:

$$D_a(p_a, p_b) = 0.5 \times \{(1 - s_i(p_a)) + s_i(p_a) \times r_i\} + 0.5 \times \{s_i(p_b) \times (1 - r_i)\} \qquad (4)$$

where $s_i(p_a) =$ probability of searching the second seller b in treatment i
$r_i =$ empirical recall propensity in treatment i

Table 4 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 and in fact, they preserve the observed price ranking. This indicates that seller pricing behavior is reasonable when the excessive search by the human buyers is taken into account.[39]

The following summarizes the results from the human buyer treatment:

[38] In case of uninformed consumers, the random effect regression includes price and match value of the assigned seller and time trend as the explanatory variables. Theory dictates the addition of the match value of the second seller in case of informed consumers.

[39] The best response calculations also show that the payoff function is quite flat. This might provide a further explanation for the low observed prices.

Result 3: Comparative statics predictions of the model do not hold. The prices and profits can be empirically ranked as MI<UI<PSMI.
Result 4: UI prices converge to the treatment-specific equilibrium prediction but the prices in MI ands PSMI treatment are significantly lower than the prediction. Variance declines over time.
Result 5: Human buyers tend to over-search compared to the optimal, which intensifies price competition among sellers. The low prices are approximately sellers' best response to the observed buyer search strategy.

VI.C Human and Robot buyer treatments

The dramatic difference in outcomes between the automated and human buyer treatments has not been observed in previous posted offer experiments with costly buyer search (Cason and Friedman, 2003) and without search (Davis and Williams, 1999). These authors find that although the results were more variable in the human buyer sessions than in the robot buyer sessions, the model's equilibrium predictions were generally supported even with human buyers. In these studies, however, sellers are unable to advertise their prices and buyers are unable to recall previously solicited offers. This limits the diffusion of information.

On the contrary, Cason and Datta's (2005 a, b) recent experiments, based on a homogeneous goods model with seller advertising and costly buyer search, provide strong evidence that human buyers' search strategies filter back into the sellers' pricing behavior in a manner that leads to lower prices. In Cason and Datta, while overly aggressive seller advertising is observed in both buyer treatments, it is higher-than-optimal search tendencies displayed by human buyers that result in a more transparent pricing environment. Sellers favor undercutting strategies to entice human buyers and eventually prices approach the full information Bertrand level of 0. In our setting, product differentiation prevents the prices from falling to the competitive level but the underlying reasoning remains the same so that strong parallels may be drawn between the two studies.

Such anomalies between human and robot buyer treatments call for further investigation. Hopkins and Seymour (2002) suggest a plausible explanation for the apparent inability of the equilibrium approach to explain market outcomes in a homogenous goods environment. They develop a learning model in this type of imperfect information game and find that the dispersed price equilibrium is not robust to the inclusion of joint buyer-seller learning dynamics. Our differentiated goods study suggests that even unique price equilibrium may not be robust to simultaneous learning by buyers and sellers.

This paves the way for future theoretical work aimed at explaining the failure of Nash equilibrium in predicting behavior. For example, observed search behavior seems to warrant modeling a mixed strategy equilibrium that incorporates Bayesian updating of 'non-optimal' buyer search. Moreover, note that in homogeneous goods setting, dispersed equilibrium prices make the inclusion of buyer dynamics both evolutionarily unstable (Hopkins and Seymour, 2002) and empirically intractable (Cason and Datta, 2005). The unique price prediction in the differentiated goods environment on the other hand, makes the analysis of buyer learning easier. Finally, from an empirical standpoint, learning dynamics in the human buyer treatment can be analyzed using behavioral models (such as imitation and reinforcement learning) and bounded rationality.

VII. Conclusion

This experimental study examines whether the content of information and the timing of its dissemination affects firms' market power. We extend the literature on consumer search costs to markets with differentiated products by testing a modified version of Anderson and Renault's (2000) model. We construct a price-setting duopoly model with costly search in which some consumers may receive costless additional information about price or product characteristics. Contrary to conventional wisdom, in this model the presence of informed consumers imparts a negative externality to the uninformed consumers by raising equilibrium prices. Additional information about product characteristics lowers the buyers' demand elasticity and results in higher price. Controlled laboratory settings allow us to induce product preferences and manipulate different informational structures. Further, it allows us to circumvent estimation problems encountered in most empirical studies which make their field comparisons untenable.

Laboratory data support the negative externality prediction when sellers face a large number of automated buyers that are programmed to follow the optimal search strategy. The prices observed in the laboratory conform to the model's comparative statics and are broadly consistent with the predicted price levels. When a small number of human buyers are used, however, the prices do not correspond to the predicted ranking. In treatments where a fraction of the consumers receive additional information about product characteristics, sellers post prices that are significantly lower than the treatment-specific prediction. This reason for this anomaly appears to lie in the in the excessive buyer search which instigates increased price competition amongst sellers. Furthermore, this aggressive price setting behavior was found to be a rational response by the sellers to the search behavior of the buyers.

Table 1: Experimental Design

2 sessions*	Uninformed (UI)	Price Informed (PI)	Match Informed (MI)	Content Matters
2 sessions*	Uninformed (UI)	Match Informed (MI)	Price Informed (PI)	
2 sessions* #	Uninformed (UI)	Match Informed (MI)	Pre-Search Match Informed (PSMI)	Timing Matters
2 sessions* #	Uninformed (UI)	Pre-Search Match Informed (PSMI)	Match Informed (MI)	

* In each robot buyer session, there are 2 independent groups of 8 subjects (16 duopoly sellers facing 200 automated buyers)

[#] In each human buyer session, there are 18 subjects with 6 duopoly sellers facing a market consisting of 4 buyers each.

Table 2: Theoretical Predictions

Information Treatment	Equilibrium Price
Price Information (PI)	57.93
No Information (UI)	68.86
Match Information (MI)	81.56
Pre-Search Match Information (PSMI)	137.71

Table 3: Mean Prices in the last 10 periods.

Treatment	Session	Sequence 1	Sequence 2	Sequence 3
UI-PI-MI	1	65.503	54.558	70.579
		66.384	57.975	73.525
	5	61.398	55.389	70.405
		66.667	60.238	69.584
UI-MI-PSMI	2	60.005	63.946	136.942
		66.274	69.361	134.536
	6	55.613	75.413	142.063
		57.343	66.265	116.291
UI-MI-PI	3	56.25	65.363	58.489
		57.075	60.885	58.3865
	7	65.522	64.157	57.305
		58.455	73.741	61.674
UI-PSMI-MI	4	71.163	132.538	105.525
		60.404	115.722	83.5265
	8	61.826	122.449	77.616
		65.691	119.527	78.527

Table 4: Mean Prices in the last 10 periods of the human buyer treatment.

Treatment	Session	UI	MI	PSMI
UI-MI-PSMI	1	64.76	55.83	71.47
UI-PSMI-MI	2	73.03	73.61	73.35
Average Price		68.90	64.72	72.41
Equilibrium Price		68.86	81.56	137.71
Best Response Price		62	55	75

Table 5: Comparison of the optimal and observed search.
(0 = no additional search and 1 = search the second seller)

Uninformed Treatment	Observed Search		
Optimal search	0	1	Total
0	43.92	17.36	61.28
1	10.42	28.30	38.72
Total	54.34	45.66	100

Match Informed Treatment	Observed Search		
Optimal search	0	1	Total
0	51.74	23.96	75.69
1	0.87	23.44	24.31
Total	52.6	47.4	100

Pre-Search Match Informed Treatment	Observed Search		
Optimal search	0	1	Total
0	69.62	29.86	99.48
1	0	0.52	0.52
Total	69.62	30.38	100

Table 6: Search errors

	Uninformed Treatment	**Match Informed Treatment**		**Pre-Search Match Informed Treatment**	
		Uninformed	Informed	Uninformed	Informed
Type 1 error	10.42	1.39	0.35	0	0
Type 2 error	17.36	26.04	21.88	47.93	11.54

Figure 1: Equililibrium Prices for different search costs

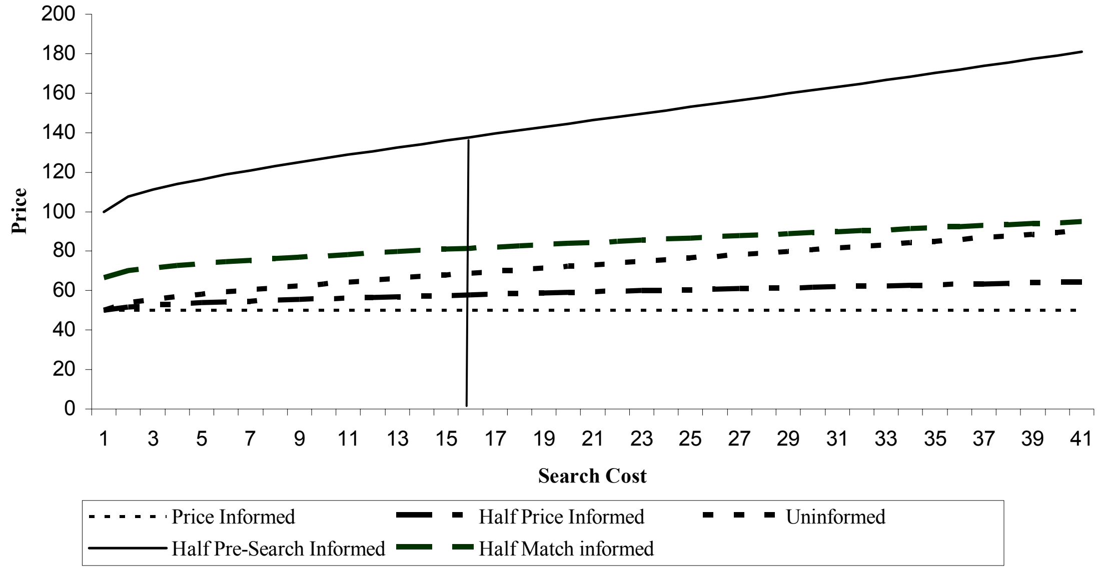


Figure 2: Average Posted Price
Sessions 1 and 5: Uninformed - Price Informed - Match Informed

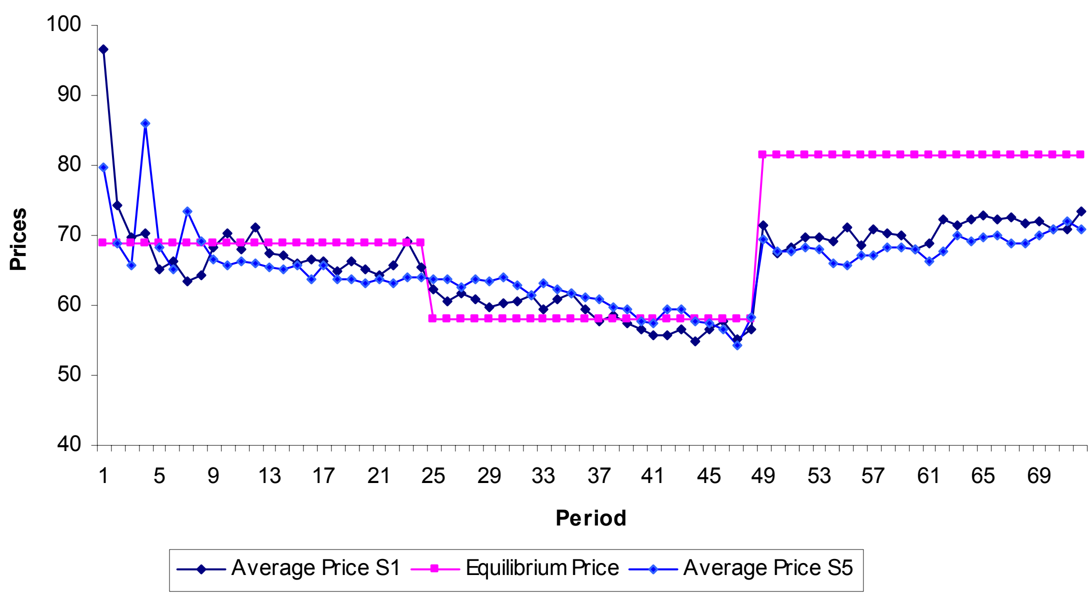


Figure 3: Average Posted Price
Sessions 2 and 6: Uninformed - Match Informed - Pre-Search Match Informed

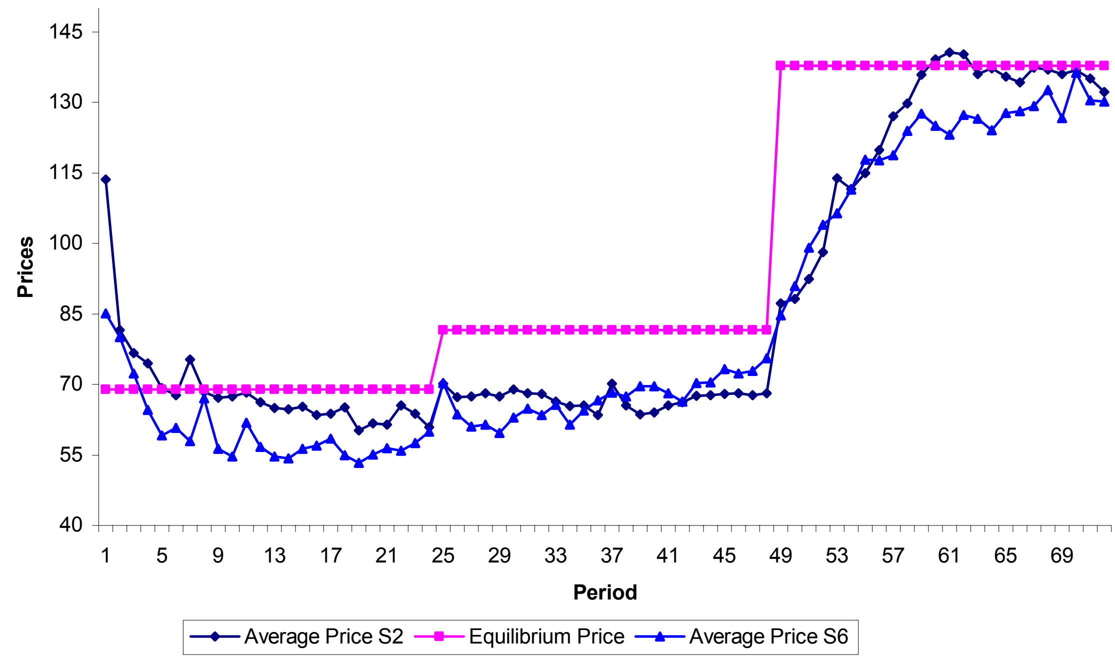


Figure 4: Average Posted Price
Sessions 3 and 7: Uninformed - Match Informed - Price Informed

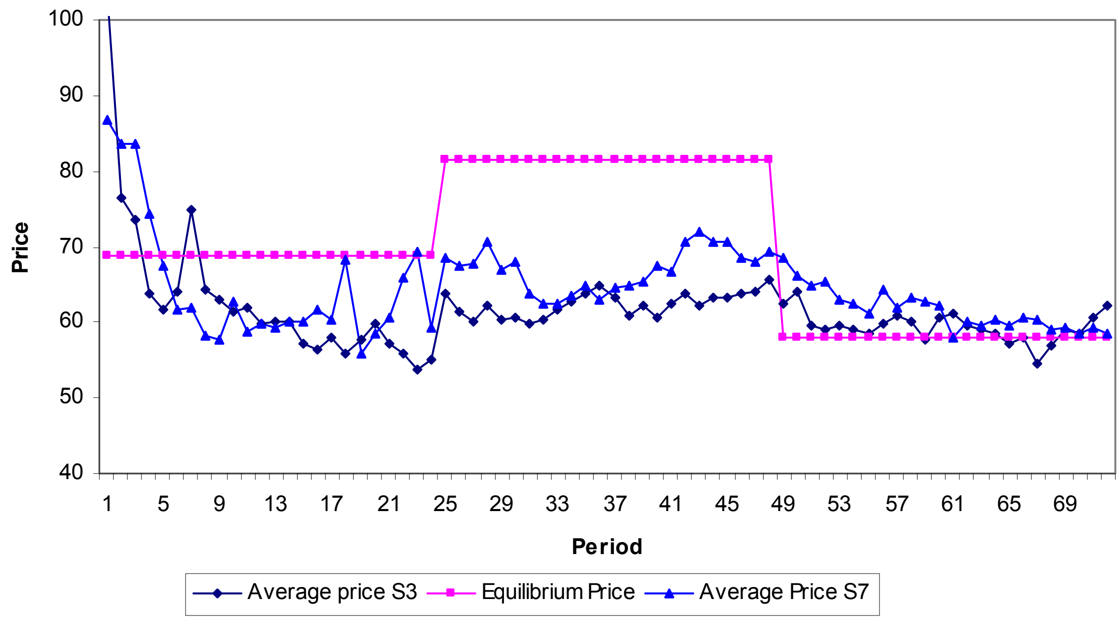


Figure 5: Average Posted Price
Session 4 and 8: Uninformed - Pre-Search Match Informed - Match Informed

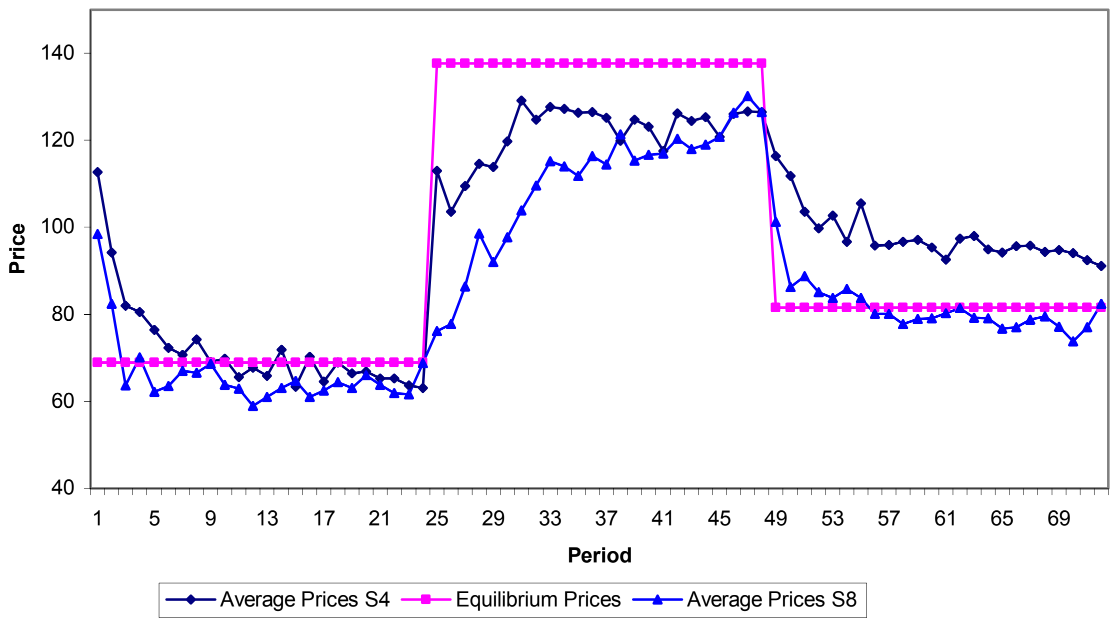


Figure 6: Average Price in the Uninformed treatment

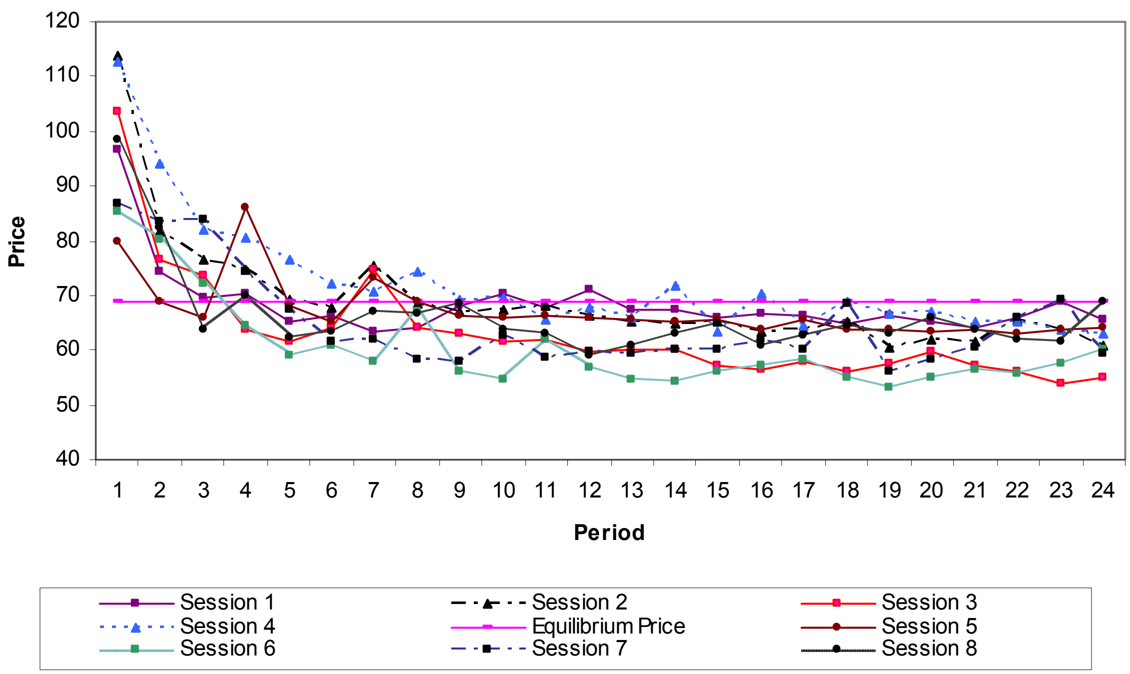


Figure 7: Average Price in the Price Informed treatment

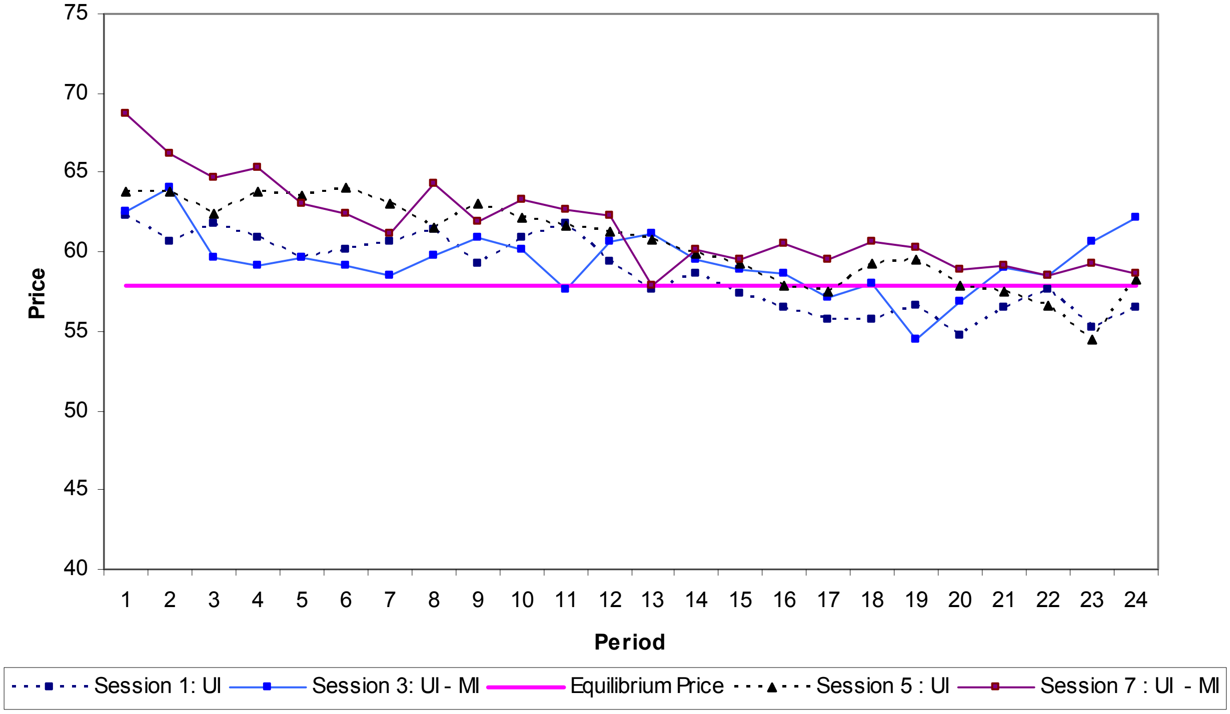


Figure 8: Average Price in the Match Informed treatment

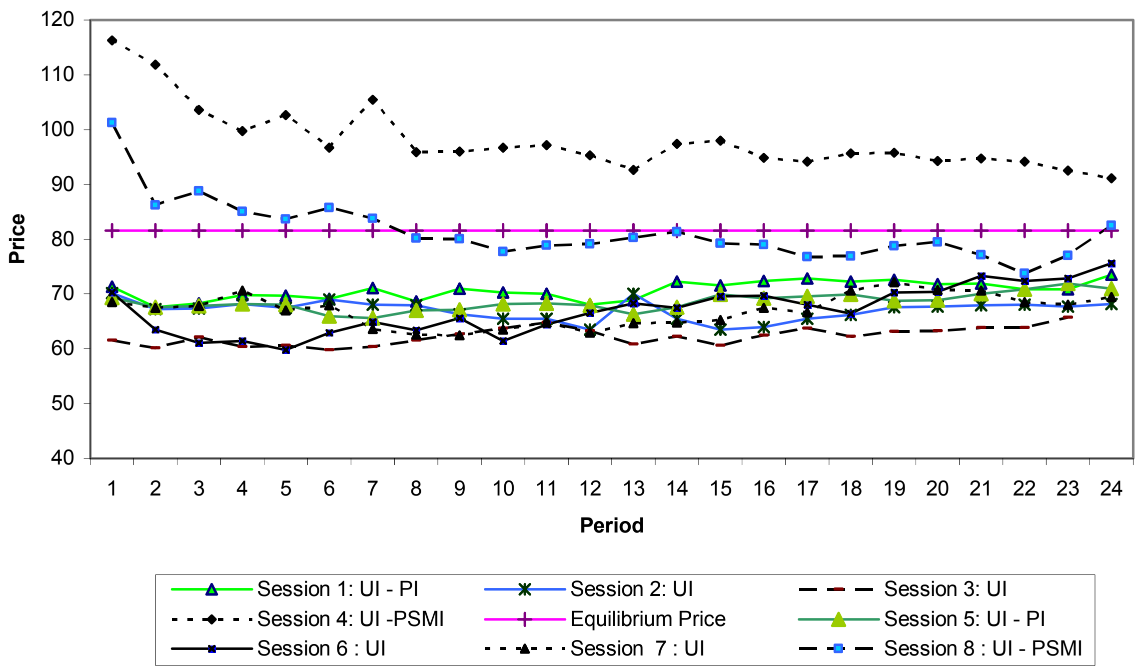


Figure 9: Average Price in the Pre-Search Match Informed treatment

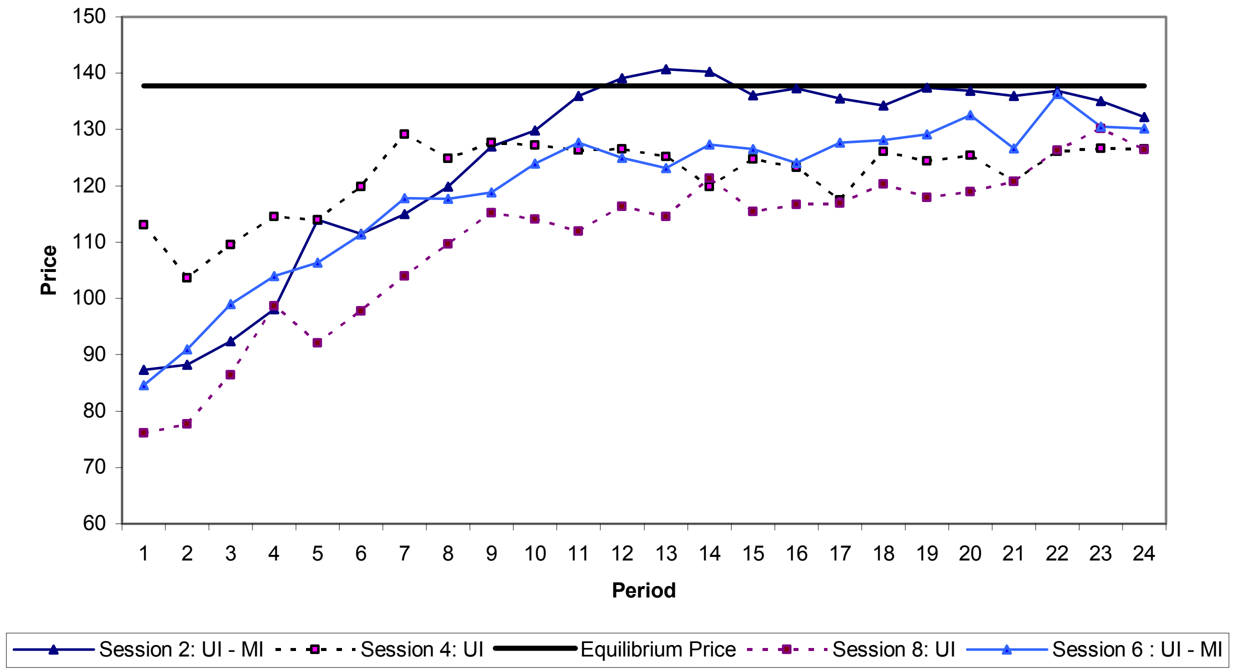


Figure 10. Average Posted Price for Human Buyer Treatment
UI - MI - PSMI

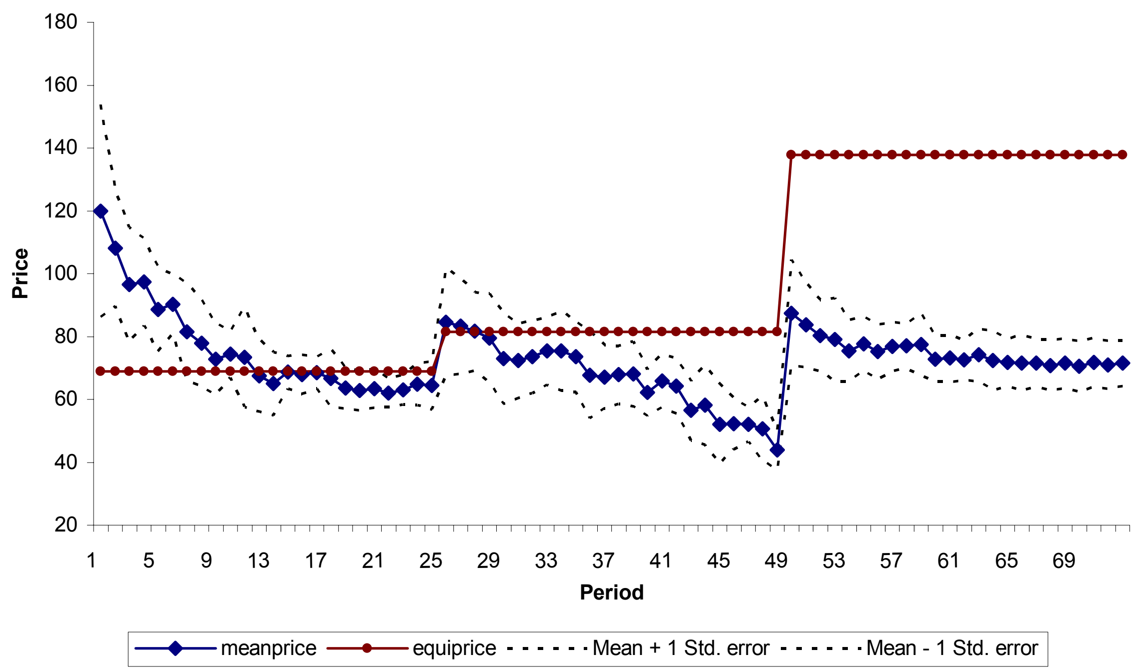


Figure 11. Average Posted Price for Human Buyer Treatment
UI - PSMI - MI

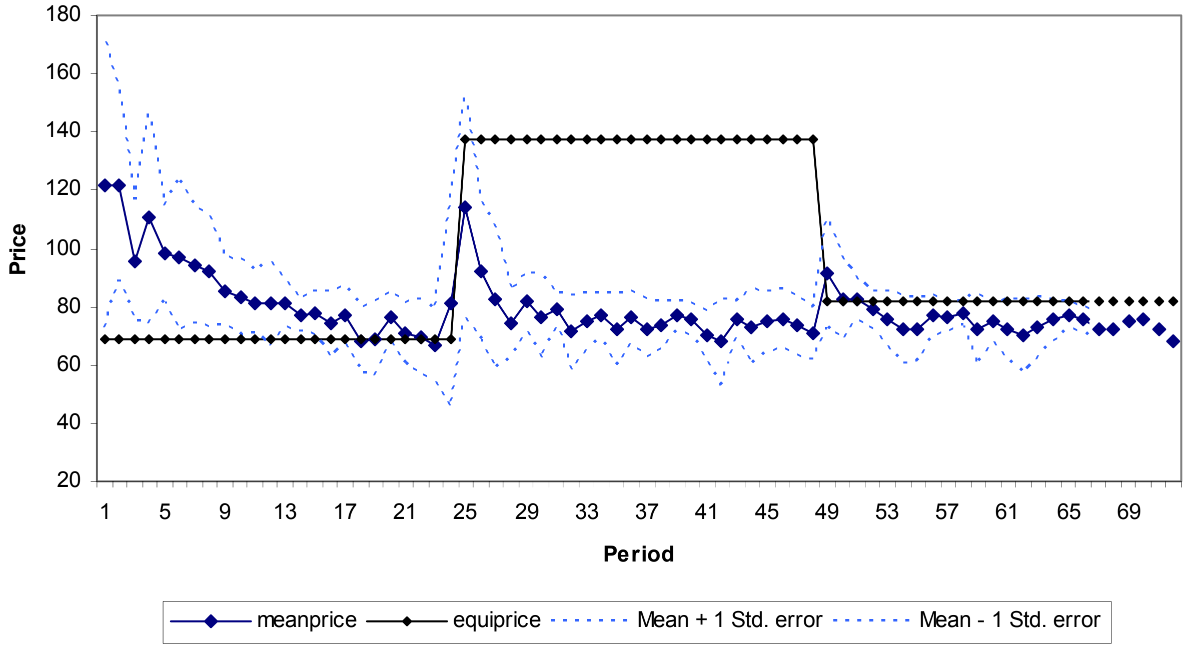
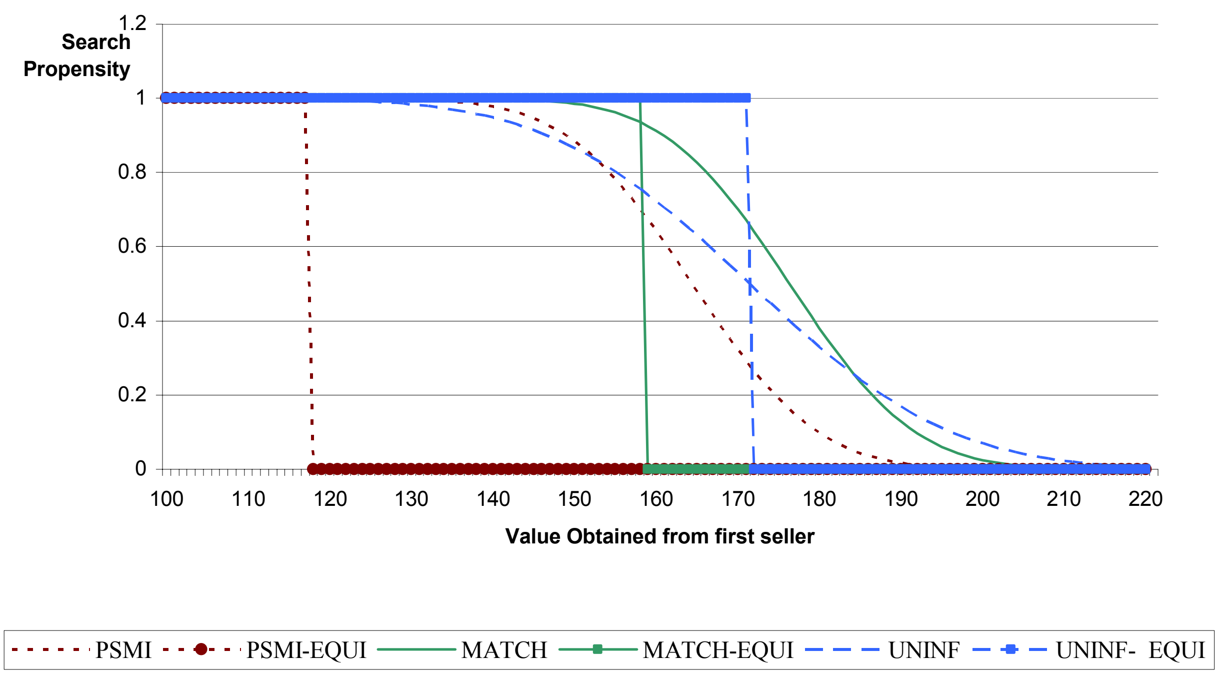


Figure 12: Optimal and Observed Search Propensity in Human Buyer Sessions



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