# An Experimental Study of Price Dispersion[*]

by

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**Abstract**

Price comparison sites have become an increasingly popular way to shop online. Yet, even though consumers have complete access to the list of prices for apparently identical products offered on these sites, persistent price dispersion has been widely observed. One important theoretical explanation for this phenomenon comes from clearinghouse models of price dispersion. These models predict that price dispersion arises because of consumer heterogeneities – some consumers are "informed" and simply buy from the firm offering the lowest price while the remaining consumers are "captive" and shop based on considerations other than price. Using a simple clearinghouse model, we derive testable comparative static implications of changes in market structure on equilibrium pricing. We show that an increase in the fraction of informed consumers leads to more competitive pricing for all consumers. Further, we show that when more firms enter the market, prices to informed consumers become more competitive, but prices to captive customers become *less* competitive. We then assess these implications in a laboratory experiment. Despite some discrepancies between predicted and pricing behavior, we find strong support for the comparative static predictions derived above.

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**JEL Classification Numbers:** C72, C92

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## 1. Introduction

One important way in which Internet retail markets differ from their brick and mortar cousins is in the prevalence of price comparison sites. One of the most popular price comparison sites is Shopper.com. This site covers over 100,000 different consumer electronics products. Figure 1 provides a screen shot of the information that a consumer obtains by accessing this site. At the top of the screen, the manufacturer and part number being offered are shown; thus consumers can be sure that they are indeed comparing prices for identical products. Below this, the prices offered by listing merchants are displayed. As the figure shows, the information on the screen presents the name of each listing merchant, the price offered, and details as to shipping costs and whether the product is in stock. All of this information is sortable by the consumer. To purchase an item, the consumer need only click the merchant's name, and she is taken to the merchant's site where the item is located.[2]

[FIGURE 1 HERE]

Of course, a substantial fraction of consumers do not shop using price comparison sites and, even of those who do, some do not appear to be motivated purely by price considerations. For instance, Brynjolfsson and Smith (2000) offer evidence of click-through rates at a price comparison site for books. They find that 16% of consumers make multiple click-throughs when visiting the site and a significant number of consumers make their last click through, which is presumably reasonably highly correlated with subsequent purchase, to a seller not offering the lowest price. In a survey, Smith, Bailey, and Brynjolfsson (1999) identify several factors such as loyalty, brand awareness, trust, and reputational considerations as possibly motivating some consumers not to purchase from the low-price

[2] Since merchants pay to list their items at the site and since there is a fee (from 40 to 75 cents) for each "lead" (in the form of a click through) provided by Shopper.com, there are substantial incentives for merchants not to misrepresent their information. See Baye, Morgan, and Scholten (2001) for additional discussion of the "seriousness" of price listings on Shopper.com.

firms. Nonetheless, consumers shopping at comparison sites seem to be unusually price sensitive. Ellison and Ellison (2001) estimate a demand elasticity of –51.8 for consumers shopping at a price comparison site for low-end computer memory.

So how competitive are prices listed on comparison sites? In a study of the top 1000 products listed on Shopper.com over a period from August 2, 2000 through March 1, 2001, Baye, Morgan, and Scholten find that on average a little more than 18 firms list prices for each product. Despite the number of firms competing in what are essentially homogeneous product markets, Baye *et al.* find the there is persistent and substantial price dispersion in these markets. Likewise, other studies of price comparison sites, such as Brynjolfsson and Smith (2000), observe substantial price dispersion.

An important equilibrium explanation of the observed price dispersion comes from "clearinghouse" models. In these models, firms list prices at some central clearinghouse for price information, such as a price comparison site. Some consumers consult these price listings and buy from the firm offering the lowest price. Other consumers shop on some other basis, such as store name recognition, branding, and so on. These consumers are essentially "captive" customers, distributed among the competing firms. In this environment, firms face a tension between posting a low price to attract consumers shopping at the comparison site and posting a high price to extract revenue from captive customers.[3] Equilibria in these models lead to a distribution of prices offered by firms. That is, these models predict persistent price dispersion for prices posted in the central clearinghouse. Models along these lines include Salop and Stiglitz (1977), Shilony (1977), Rosenthal (1980), Varian (1980) and Baye and Morgan (2001).

[3] These models assume that a firm can post a single price, and so cannot price discriminate between the two types of consumer. Interestingly, at least for firms listing prices on Shopper.com, Baye *et al.* report finding little evidence of price discrimination.

In Section 2, we study a simple clearinghouse model and derive comparative static implications of changes in market structure on equilibrium pricing. In particular, as the proportion of informed buyers increases, the prices paid by both informed buyers and captive customers are predicted to decrease. That is, the market gets more competitive. In contrast, as the number of competing sellers increases, the price paid by informed buyers declines, but that paid by captive customers *increases.* Thus, the model delivers the counterintuitive prediction that increased competition in fact raises prices to a portion of the consumers.

These theoretical findings potentially have important implications for government policies related to promoting the Internet. In particular, policies designed to bridge the "digital divide" by providing universal Internet access are pro-competitive since they presumably increase the fraction of "informed" consumers. Moreover, this policy creates a positive externality, lowering the prices paid by customers still on the wrong side of the divide. On the other hand, issues such as tax exemption for Internet transactions, which may have the effect of spurring entry into E-commerce, need not be socially beneficial. Although such initiatives are predicted to lead to lower prices for informed consumers, the remaining consumers might actually be hurt by this policy in the form of higher prices.

So how seriously should one take these theoretical implications? To date, clearinghouse models have received little empirical investigation. Villas-Boas (1995) directly tests Varian's model using data from the coffee and saltine cracker markets. He finds that the marginal distributions of prices in some markets are indeed consistent with that predicted by the model. However, estimates of structural cost parameters vary widely across similar products, raising some questions about the empirical validity of the model. More recently Kessner and Polborn (2000) use the effects of changes in tax policy on prices in the German life insurance industry to test whether price dispersion is best explained by imperfect consumer information or product heterogeneity. They conclude that at least part of the observed price dispersion cannot be explained by product heterogeneity, but rather is a consequence of imperfect consumer information.

The paucity of empirical studies in this area may reflect the difficulties of assessing these models using field data. Laboratory methods, on the other hand, are ideally suited to assessing these models, since they offer an opportunity to control two sets of relevant variables.

First, the equilibrium pricing strategies depend on the fraction of consumers using the comparison site to shop, the reservation prices of the consumers, the cost structures of the competing firms, and the number of potential competitors. In an experiment, these variables can be controlled and manipulated, whereas these variables are often difficult to observe and measure in the field.

Second, field data will typically reflect several sources of price dispersion. For example, merchants listing prices on Shopper.com differ slightly in their arrangements for restocking in the event of a return, in customer service, in their general reputation for reliability, in their inventory costs, and on a host of other factors. While such product heterogeneity is clearly important in field settings, the clearinghouse models suggest it is not necessary to generate equilibrium price dispersion.[4] In laboratory experiments we are able to focus on how changes in consumer search technologies affect price dispersion, and minimize such confounding factors as product heterogeneity.

In Section 3, we describe an experiment designed to test the clearinghouse model predictions. To the best of our knowledge, we are the first to assess the plausibility and implications of these models experimentally. As noted, of particular interest is the effect of variation in the competitive structure of the market on price levels. We consider two types of

[4] As Stigler (1961, p. 214) points out there is never absolute homogeneity of commodities in naturally occurring markets. However, he regards price dispersion as primarily reflecting ignorance in the market; he states "…a portion of the observed dispersion is presumably attributable to such [product] differences. But it would be metaphysical, and fruitless, to assert that all dispersion is due to heterogeneity."

variation: First, we vary the number of competing sellers in the market—in one treatment using two sellers and in another treatment using four sellers. Second, we vary the proportion of "informed" buyers—in one treatment using equal numbers of informed and captive buyers, and in another treatment using five informed buyers per captive buyer.

Section 4 presents our results. In all treatments, we observe, as predicted, persistent price dispersion and pricing above marginal cost by sellers, and we find strong support for the comparative static predictions of the model. When the proportion of informed buyers increases, prices to all buyers fall. In particular, prices to informed buyers decline by 46% in the Two-seller treatment and by 51% in the Four-seller treatment, while prices to captive customers decline by 35% and 20%, respectively. When the number of sellers increases from two to four, prices to informed buyers fall while those paid by captive consumers increase. In particular, prices to informed buyers decline by 36% (when there are equal numbers of informed and captive buyers) and 42% (when five in six buyers are informed), while prices to captive customers *increase* by 7% and 31%, respectively. Thus, in terms of predicting the direction in which prices move in response to underlying changes in the market structure, the model performs extremely well.

However, we do find some systematic discrepancies between theoretical and observed price distributions. In the two seller treatments, observed average prices are consistently higher than that predicted by theory. In the four seller treatments, prices tended to be more dispersed than the theory predicts. Section 5 explores possible explanations for these discrepancies. Finally, Section 6 concludes.

## 2. Theory

### 2.1 A Simple Clearinghouse Model

Consider a market where $n$ identical firms compete to supply some product. Each firm has a constant marginal cost, which we normalize to be zero and no fixed costs or capacity constraints. Firms simultaneously choose prices. Let $p_i$ be the price chosen by firm $i$.

Demand in this market comes from a continuum of consumers normalized to mass equaling one, who each demand one unit at any price not exceeding a reservation price of $r$. We also normalize $r$ to be 1. A fraction, $l$, of consumers freely obtain access to the full list of prices offered by firms. These consumers buy from the firm offering the lowest price, provided this price does not exceed the reservation price. The remaining customers, whom we call captive customers, are evenly distributed among the competing firms and purchase if the firm to which they are "loyal" offers a price less than the reservation price. Thus, a firm can expect to sell to $(1-l)/n$ captive customers as long as its price does not exceed 1.[5]

Firms choose prices to maximize expected profits. Let $p_{-i}$ denote the set { $p_1$, $p_2$, …, $p_{i-1}$, $p_{i+1}$,…, $p_n$}. Thus, the expected profit of firm $i$ when it chooses price $p$ is

$$p_i(p) = \begin{cases} p(l + (1-l)/n) & \text{if } p < \min p_{-i} \\ p(l/m + (1-l)/n) & \text{if } i \text{ is tied with } m \text{ firms for the lowest price} \\ p(1-l)/n & \text{if } p > \min p_{-i} \end{cases}.$$

This model is closely related to Varian (1980). The main differences are that we fix the number of competing firms exogenously, enabling direct comparative static analysis with respect to the number of competing firms. (Varian determines the number of competing firms

[5] A variety of interpretations may be given to the behavior of captive consumers. For instance, they may not have access to or be aware of the price comparison site. Alternatively, they may have access to the site, but be primarily motivated by considerations other than price, such as branding or reputation.

according to a zero profit condition.) We also assume constant marginal costs (which we normalize at zero) and no fixed costs.[6]

A symmetric equilibrium involves mixed strategies where each firm prices according to a continuous cumulative distribution $F$ on the interval $[p_0, 1]$. Expected profits for all prices in the support of $F$ must be

$$p_i(p) = p_i(1),$$

or, equivalently,

$$p\left(l + \frac{1-l}{n}\right)(1-F(p))^{n-1} + p\frac{(1-l)}{n}\left(1-(1-F(p))^{n-1}\right) = \frac{1-l}{n}.$$

Rearranging yields

$$F(p) = 1 - \left(\frac{(1-l)(1-p)}{npl}\right)^{\frac{1}{n-1}} \text{ for } p \in [p_0, 1],$$

where the lower bound of the support, $p_0$, must satisfy $F(p_0) = 0$, or

$$p_0 = \frac{1-l}{nl+1-l}.$$

In summary,

**Proposition 1.** A symmetric equilibrium in the model entails all firms pricing according to the cumulative distribution $F(p) = 1 - \left(\frac{(1-l)(1-p)}{npl}\right)^{\frac{1}{n-1}}$ on the support $[p_0, 1]$, where $p_0 = \frac{1-l}{nl+1-l}$.

**Proof.** See Appendix A.

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[6] This cost structure seems roughly consistent with that faced by e-retailers who have, essentially, a constant marginal cost per unit sold. Of course, fixed costs are a significant expense for e-retailers as well. Nonetheless, since in equilibrium firms earn positive economic profits, our results are robust to the inclusion of positive fixed costs.

In studying this model in a laboratory setting, we will mainly be interested in comparative statics relating to the competitiveness of prices; that is, the expected prices paid by informed and captive consumers. Recall that the expected price paid by informed consumers is the expectation of the lowest price offered by the *n* competing firms. We denote this by $E(p_{\min})$. In contrast, the expected price paid by captive consumers is simply the expected value of a single draw from *F*, or $E(p)$. We focus on how these vary in response to changes in the proportion of informed consumers, $l$, and the number of firms, *n*.

## 2.2 Changes in the Proportion of Informed Consumers

As access to the Internet becomes increasingly widespread, we would expect that the proportion of informed consumers as a fraction of the population would be increasing. What impact does this have on prices for those consumers on both sides of the digital divide? We show that an increase in the fraction of informed consumers lowers prices to both informed and captive consumers. Formally,

**Proposition 2.** As the fraction of informed consumers increases, the expected prices paid by both informed and captive consumers decrease.

**Proof.** See Appendix A.

To obtain some intuition for this result, notice that, as the fraction of informed consumers increases, price reductions to attract these customers become relatively more attractive to firms. At the same time, the reduction in the fraction of captive customers available to each firm means that the cost of these price reductions, in terms of foregone revenues from captive customers, is now lower. The upshot is that each firm’s distribution of prices when a smaller fraction of consumers are informed stochastically dominates the price distribution when a larger fraction is informed.

**2.3 Changes in the Number of Competing Firms**

Over the last several years, the number of e-retailers has grown exponentially. What is the impact of this growth on pricing for both informed and captive consumers? In this subsection, we show that while this growth in the number of competing firms is helpful to informed consumers, the model predicts that it is *harmful* to captive consumers. In other words, while increases in the number of competing firms lower the expected price to informed consumers, the expected price paid by captive consumers *increases*.

To see this, we first show that $E(p_{\min})$ and $E(p)$ move in opposite directions with respect to $n$. In particular (see Appendix A),

$$\frac{dE(p_{\min})}{dn} = -\left(\frac{1-l}{l}\right)\frac{dE(p)}{dn}.$$

This differs from a result in Rosenthal (1980). Rosenthal shows that the expected price paid by both informed and captive consumers move in the same (increasing) direction as a function of the number of competing firms. A key difference between the two models is that, in Rosenthal, an increase in the number of firms is accompanied by an increase in the number of captive consumers so that each firm retains a constant number of captive consumers. As a result, the stiffer competition for the informed consumers makes offering discounted prices in hopes of attracting them, less attractive relative to simply capturing the surplus from the captive consumers. This drives up the expected prices to both types of consumers.

In our model, entry leads to a reduction in each firm's share of the captive consumers and to stiffer competition for informed consumers. Thus, firms are being tugged in opposite directions. Catering solely to the captive consumers is a less profitable strategy with a larger number of firms. At the same time, competition for informed consumers grows stiffer with firm entry, so it too is a less attractive market.

We show in Appendix A that $E(p)$ increases with $n$. This combined with the observation that prices move in opposite directions for informed and uninformed consumers demonstrates

**Proposition 3.** As the number of firms increases, the expected price paid by informed consumers decreases and the expected price paid by captive consumers increases.

**Proof.** See Appendix A.

## 3. Experiment

In this Section, we describe in detail the procedures and parameters used in the experimental sessions.

### 3.1 Parameters

The model described in the previous section delivers clear comparative static predictions for the effects of changes in the market structure (i.e. changes in $n$ or $l$) on prices to informed buyers and prices to captive consumers. We test these predictions by varying the number of sellers at two and four, and the proportion of informed buyers at 1/2 and 5/6 of the population. Table 1 presents theoretical predictions of the prices to informed and captive consumers under our experimental conditions as well as under some alternative parameter configurations.

Table 1. Theoretical Predictions for Alternative Parameter Values

| | | $l$ = 0/6 | $l$ = 1/6 | $l$ = 2/6 | $l$ = 3/6 | $l$ = 4/6 | $l$ = 5/6 | $l$ = 6/6 |
|---|---|---|---|---|---|---|---|---|
| $E(p)$ | $n = 2$ | 1 | 0.841 | 0.693 | 0.549 | 0.402 | 0.240 | 0 |
| | $n = 4$ | 1 | 0.859 | 0.748 | 0.648 | 0.545 | 0.421 | 0 |
| $E(p_{\min})$ | $n = 2$ | 1 | 0.794 | 0.614 | 0.451 | 0.299 | 0.152 | 0 |
| | $n = 4$ | 1 | 0.703 | 0.504 | 0.352 | 0.228 | 0.116 | 0 |

We consider the situation where there are two competing sellers and where half the buyers are informed to be a natural benchmark treatment. As Table 1 shows, relative to this benchmark, doubling the number of sellers is predicted to increase the mean price paid by captive customers by 18% and decrease that paid by informed buyers by 22%. Increasing the fraction of informed buyers to 5/6 lowers the expected price they pay (relative to the benchmark) by 66% while also lowering the price paid by captive customers by 56%.

As we report below, with the parameters $n$ = 2, 4, and $l$ = 1/2, 5/6, our experimental design effectively separates treatments in the sense that if the theoretical model correctly describes pricing behavior, the comparative static tests that we employ lead to correct inferences with probabilities close to one.

The main advantages of our chosen parameterization over the other alternatives we considered are as follows:

1. If the fraction of informed consumers is too low, detecting the effect of changes in the number of sellers on price levels becomes increasingly difficult. For instance, when the fraction is only 1/6, doubling the number of sellers from 2 to 4 results in virtually no change in the average price paid by informed and captive consumers. Similarly, at both extremes – where all consumers are informed or none are – changing the number of sellers is predicted to have no effect whatsoever.
2. Relative to the benchmark, doubling the number of sellers ensures a large enough predicted effect to be at least in principle observable in the data.

### 3.2 Procedures

The experiment consisted of 12 sessions conducted at the University of Nottingham in Spring 2001. Six sessions employed a Two-seller treatment, while the other six employed a Four-seller treatment. The differences between these treatments are indicated below, otherwise all sessions used identical procedures.[7]

Subjects were recruited from a distribution list comprised of undergraduate students from across the entire university who had indicated a willingness to be paid volunteers in decision-making experiments, where participants earn on average between £6 and £12 per hour, depending on the experiment. For this experiment subjects were sent an e-mail invitation promising to participate in a session lasting approximately 90 minutes, for which they would receive a £3 show-up fee plus "an additional amount that would depend on decisions made during a session."[8]

Twelve subjects participated in each session, and no subject appeared in more than one session. Throughout the session, no communication between subjects was permitted, and all choices and information were transmitted via computer terminals. At the beginning of a session, the subjects were seated at computer terminals and given a set of instructions, which were then read aloud by the experimenter.[9]

The session then consisted of three phases of thirty periods each. At the beginning of each period, subjects were randomly assigned to groups of either two (Two-seller sessions) or four (Four-seller sessions) sellers, and then simultaneously chose prices from the set {0, 1, 2, …, 100}.[10] Each group faced six computerized buyers who bought twelve units each. Some of these buyers corresponded to the informed buyers of Section 2 and were programmed to buy all twelve units from whichever seller charged the lowest price. (In the case of ties for the lowest price, purchases were divided equally among the tied sellers.) The remaining buyers

[7] We also conducted two pilot sessions using graduate students - these are reported in Appendix B.
[8] At the time of the experiment the exchange rate was approximately £1 = $1.42.
[9] Appendix C contains copies of the instructions.
[10] Notice that one way in which the experimental implementation of the clearinghouse model differs from theory is that subjects choose from a discrete rather than a continuous set of prices. For our benchmark treatment, we computed the exact symmetric equilibrium for the discrete case. The difference between this equilibrium and that predicted when the choice set is continuous is negligible: for example, the expected price is about half a percent higher in the discrete case.

corresponded to the captive buyers, and bought six units (Two-seller) or three units (Four-seller) from each seller. After all subjects had submitted their prices, profits for each seller, denominated in ‘points’, were calculated as (price × quantity). At the end of each period a ‘Results Screen’ was displayed on each terminal. This screen listed all prices submitted in the period, together with the associated quantities, highlighting the prices and quantities for that subject’s competitor(s). The screen also informed subjects of their own point earnings for that period, the previous five periods, as well as accumulated point earnings. A sample ‘Results Screen’ is shown in Figure 2.

[FIGURE 2 HERE]

In the first phase of thirty periods, groups faced three informed and three captive buyers. In the second phase (periods 31-60) the proportion of informed buyers was increased to five of six, and in the third phase (periods 61-90) the proportion was decreased back to three of six. This information was described in the instructions, and was also given on the screen that prompted subjects for their pricing decision.

At the end of the session, subjects were paid the show-up fee plus 1p per 100 points accumulated over all ninety periods. Earnings averaged £17.96 (Two-seller sessions) and £9.33 (Four-seller sessions) for sessions lasting between 50 and 80 minutes. At the end of the session, subjects also completed a short post-experimental questionnaire and the question “Would you be willing to take part in other experiments of this sort?” received 144 out of 144 affirmative responses.

In arriving at these procedures, we considered a number of issues regarding the number of periods and the nature of the feedback, the computerized nature of the buyers, and the way in which subjects were rewarded.

Given the complexity of calculating the equilibrium distribution, we did not expect strategies to conform to equilibrium predictions at the outset of a session. Rather we envisaged that subjects may develop a sense of what were good and bad strategies as they gained experience with the environment, and received feedback on others' decisions.

We considered several alternative ways to give feedback to subjects. In an experimental study of markets with costly search, Abrams, Sefton and Yavas (2000) had sellers repeatedly post prices over 25 market periods, but did not reveal to sellers the prices posted by other sellers throughout a session. (Sellers did however get some feedback in the form of buyers' responses to their price decisions.) In their experiment, prices deviated significantly from predicted levels, even in later periods. In contrast, in another experiment on costly buyer search, Cason and Friedman (2000) found much stronger support for theoretical mixed strategy predictions. In their setup, at the end of each period a seller received information about the entire distribution of prices. Since we find it plausible that part of the difference in results from the two studies reflects differences in feedback opportunities, and since we wanted to give the theoretical model its 'best shot', we adopted the Cason and Friedman procedure. Thus, we had subjects repeatedly post prices over ninety periods (as many as were feasible in a ninety-minute session), and, at the end of each period, informed subjects of all prices posted.

Our use of computerized buyers also mimics one of Cason and Friedman's procedures. In Abrams *et al.*, price predictions yielded an extremely inequitable distribution of the gains from trade. In their 'Bertrand' treatment, prices were predicted to give all the gains from trade to buyers, while in their 'Monopoly' treatment prices were predicted to give all gains from trade to sellers. In fact, observed prices resulted in a more equitable distribution, and in the monopoly treatment especially, human buyers appeared to resist high prices, often rejecting profitable transactions. Thus distributional concerns appear to have complicated the strategic issues in the Abrams *et al.* experiment. Cason and Friedman's use of robot buyers in some of their treatments effectively eliminated these distributional concerns. An additional advantage of adopting their procedure was that it simplified considerably the instructions and environment faced by subjects.

One drawback of this design is that it could, in principle, introduce unintended repeated game effects. For example, subjects may coordinate on collusive strategies whereby they all charge the monopoly price, and punish defectors by reverting to low prices. In order to mitigate such factors, we anonymously and randomly matched subjects throughout the session and prevented communication among subjects. These design factors make it extremely difficult to implement strategies designed to “punish” a particular player for past transgressions. As we report in the next section, aggregate behavior seems broadly consistent with many of the predictions of the static model but inconsistent with monopoly pricing with occasional “punishment” intervals.

We also noted that the theoretical price distribution is derived under the assumption of risk neutrality. One approach to dealing with the possibility that subjects are risk-averse is to employ a binary lottery procedure to induce (theoretically) risk neutral preferences. The drawback of this procedure is that it requires more complicated instructions and places higher cognitive demands on subjects. In fact, Selten, Sadrieh, and Abbink (1999) find subjects’ decisions are less consistent with expected value maximization when the procedure is used than when subjects are paid directly in cash. For this reason we decided against using the binary lottery procedure, preferring instead to keep the experimental environment as simple as possible. We return to the issue of risk aversion in Section 5 of the paper.

### 3.3 Hypotheses

The design of our sessions allows formal tests of the comparative static predictions presented in Section 2. In all cases these are non-parametric tests applied to *session-level* data. Our null hypotheses state that changes in the market structure (i.e. in $n$ or $l$) have no impact on prices, and we test these against one-sided alternative hypotheses suggested by the model.

For testing the prediction that increasing the number of sellers raises the expected price paid by a captive consumer, we first average prices over the first phase of each session, and then compare the set of six averages from Two-seller sessions with that from Four-seller sessions using a one-sided Wilcoxon rank-sum test. We then repeat these tests for the other two phases.

For testing the prediction that increasing the proportion of informed sellers lowers expected prices, we consider the change in average price between phases one and two for each Two-seller session, and employ a binomial test. Under the null hypothesis that prices are determined in the same way in the two phases, we would expect the average price to be equally likely to rise or fall. We reject the hypothesis if average prices fall in sufficiently many sessions. Similarly, we consider tests based on changes between phases two and three, and between phases one and three. (In the latter case, the model predicts no difference between phases, and so we employ a two-sided test). We then repeat all these tests for the Four-seller sessions.

Tests concerning effects on the expected minimum price, the price paid by informed buyers, are conducted in a similar way, using a single estimate of the mean minimum price for each phase of each session. To compute this, we first estimate the expected minimum price in a single period. Rather than use the average of the observed minimum prices, which depends on the *ex post* matching of subjects into groups of competitors, we compute the average over all possible matchings. This gives an estimate for each period, and we then average these estimates over all thirty periods to get a single estimate of expected minimum price for that phase of the session.

In addition to testing these price predictions, we used analogous methods to examine the comparative static predictions of the model for one commonly used empirical measure of price dispersion, the coefficient of variation (see Carlson and Pescatrice, 1980), hereafter referred to as ‘CV’. Again, we obtain a single measure of price dispersion for each phase of each session, by averaging the CVs from separate periods, and apply Wilcoxon rank-sum tests to these session-level data.

The advantage of this approach to analyzing the data is that it does not rely on any assumptions about the underlying data generation process within a session. We expect subjects to learn as they make decisions repeatedly, and we expect subjects to react to other subjects’ decisions. Thus, while we have many observations per session, these observations should not be viewed as independent. On the other hand, we regard any summary statistic constructed from a single session to be independent from those constructed from other sessions. Thus, our approach yields exact tests without imposing strong assumptions about how subject choices are related to one another.

The disadvantage of this approach is that the tests are based on relatively few observations - for example the test of whether reducing the number of informed buyers reduces the expected price when there are two sellers is based on just six observations. Nevertheless, we used simulations to investigate the power of the tests when prices are generated according to the theoretical model. In all cases, the power of the test is extremely close to one. Thus, our design delivers high probabilities of rejecting the null hypotheses when the theoretical model is correct.

## 4. Results

Recall that the average price paid by captive customers should, in theory, increase with the number of sellers, and decrease with the proportion of informed buyers. Figure 3 displays five-period moving averages of prices in the Two- and Four-seller treatments, together with the theoretical predictions.

[FIGURE 3 HERE]

Comparing these averages across the three phases, we observe clear shifts in the predicted directions. Prices tend to be higher in the Four-seller sessions, and tend to be lower in phase two than the other phases. Formal tests are based on the average prices within a phase of a session, as tabulated in Table 2.

Table 2. Average Prices

| | Two-seller sessions | | | | | | Four-seller sessions | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 1 | 2 | 3 | 4 | 5 | 6 | p-val |
| Phase | | | | | | | | | | | | | |
| 1 | 59.57 | 55.36 | 60.72 | 63.54 | 58.02 | 63.04 | 63.81 | 58.83 | 64.45 | 68.84 | 70.59 | 62.03 | 0.032 |
| 2 | 42.05 | 30.19 | 43.18 | 41.24 | 44.93 | 36.21 | 49.02 | 45.87 | 54.04 | 58.36 | 52.38 | 51.59 | 0.001 |
| 3 | 61.75 | 61.13 | 63.62 | 59.49 | 60.14 | 60.11 | 66.86 | 64.14 | 64.01 | 63.84 | 66.21 | 64.00 | 0.001 |

In fact, for all three phases the null hypothesis of no comparative static effect can be rejected at conventional significance levels on the basis of a Wilcoxon rank-sum test. The p-value indicates the probability under the null hypothesis of obtaining a sum of ranks at least as large as that observed (where a rank of 1 is assigned to the session yielding the lowest average price and the sum is based on the ranks of the Four-seller sessions).

Next, we test whether varying the proportion of informed buyers has the predicted effect. Our tests are based on the changes in average prices between phases, as tabulated in Table 3.

| Table 3. Change in Average Prices between Phases | | | | | | |
|---|---|---|---|---|---|---|
| | Two-seller sessions | | | Four-seller sessions | | |
| | Phase 2 – 1 | Phase 3 – 2 | Phase 3 – 1 | Phase 2 – 1 | Phase 3 – 2 | Phase 3 – 1 |
| Session | | | | | | |
| 1 | –17.52 | 19.70 | 2.18 | –14.79 | 17.84 | 3.05 |
| 2 | –25.17 | 30.94 | 5.77 | –12.96 | 18.27 | 5.31 |
| 3 | –17.54 | 20.44 | 2.90 | –10.41 | 9.97 | –0.44 |
| 4 | –22.30 | 18.25 | –4.05 | –10.48 | 5.48 | –5.00 |
| 5 | –13.09 | 15.21 | 2.12 | –18.21 | 13.83 | –4.38 |
| 6 | –26.83 | 23.90 | –2.93 | –10.44 | 12.41 | 1.97 |
| p-value | 0.016 | 0.016 | 0.688 | 0.016 | 0.016 | 1.000 |

Consider the first column. This lists the changes in average prices between phases one and two for each Two-seller session. A binomial test easily rejects the null hypothesis that average prices are equally likely to rise or fall in favor of the alternative (suggested by the theoretical model) that average prices are more likely to fall. (The probability of observing six negative signs, under the null hypothesis is 0.016.) Similarly, the changes between phases two and three support the prediction of the theoretical model. Likewise, the data from the Four-seller sessions support the theoretical predictions. Thus, in all cases, expected prices change with the proportion of informed buyers in the direction predicted by the model.

Next, we turn to the expected price paid by informed buyers, the expected minimum price. This is predicted to be higher in the Two- than Four-seller treatment, and to be lower in phase two than the other phases. Figure 4 displays 5-period moving averages of the estimated expected minimum price for the Two- and Four-seller sessions. As with the average price, the data appear to move in the directions predicted by the model.

[FIGURE 4 HERE]

Consider first the effect of the number of sellers. As before, we use one-sided Wilcoxon rank-sum tests applied to session-level data. Table 4 lists the estimated expected minimum price for each phase of each session. For all three phases, the tests applied to these data reject the null hypothesis of no treatment effect.

| Table 4. Average Minimum Prices | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Two-seller sessions | | | | | | Four-seller sessions | | | | | | p-val |
| | 1 | 2 | 3 | 4 | 5 | 6 | 1 | 2 | 3 | 4 | 5 | 6 | |
| Phase | | | | | | | | | | | | | |
| 1 | 48.12 | 44.90 | 48.04 | 52.41 | 44.89 | 52.68 | 28.04 | 28.49 | 31.29 | 33.08 | 37.59 | 30.05 | 0.001 |
| 2 | 28.15 | 18.76 | 30.30 | 25.84 | 31.39 | 24.79 | 13.96 | 11.25 | 18.34 | 18.65 | 14.58 | 16.27 | 0.001 |
| 3 | 49.68 | 50.77 | 50.93 | 48.76 | 49.62 | 50.10 | 33.74 | 30.61 | 31.64 | 31.16 | 33.04 | 30.58 | 0.001 |

To formally test the comparative static prediction concerning $l$, we look at changes in the estimates from phase to phase (Table 5). For both the $n$ = 2 and $n$ = 4 parameterizations, we reject the null hypothesis in favor of the theoretically predicted effect that $l$ and the expected minimum price move in opposite directions.

| Table 5. Change in Average Minimum Prices between Phases | | | | | | |
|---|---|---|---|---|---|---|
| | Two-seller sessions | | | Four-seller sessions | | |
| | Phase 2 – 1 | Phase 3 – 2 | Phase 3 – 1 | Phase 2 – 1 | Phase 3 – 2 | Phase 3 – 1 |
| Session | | | | | | |
| 1 | –19.97 | 21.53 | 1.56 | –14.08 | 19.78 | 5.70 |
| 2 | –26.14 | 32.01 | 5.87 | –17.24 | 19.36 | 2.12 |
| 3 | –17.74 | 20.63 | 2.89 | –12.95 | 13.30 | 0.35 |
| 4 | –26.57 | 22.92 | –3.65 | –14.43 | 12.51 | –1.92 |
| 5 | –13.50 | 18.23 | 4.73 | –23.01 | 18.46 | –4.55 |
| 6 | –27.89 | 25.31 | –2.58 | –13.78 | 14.31 | 0.53 |
| p-value | 0.016 | 0.016 | 0.688 | 0.016 | 0.016 | 0.688 |

A commonly used measure of price dispersion in empirical studies is the coefficient of variation. It is straightforward to calculate theoretical predictions for our parameter values (see Appendix A). For our parameters, the predicted values for the Two-seller treatment are 32.5% (phases one and three) and 76.0% (phase two). The predicted values for the Four-seller treatment are 43.3% (phases one and three) and 82.0% (phase two). Thus for both Two- and Four- seller treatments the model predicts a large increase in price dispersion as $l$, the proportion of informed buyers, increases from 1/2 to 5/6. For these values of $l$, the model also predicts a somewhat milder increase in price dispersion as the number of sellers doubles from 2 to 4.

To estimate the CV from our data we calculate a CV for each period by dividing the sample standard deviation of the twelve prices by their average, and then, for each phase of each session, we take the average coefficient over the thirty periods. The estimates are listed in Table 6, and the changes in these estimates across phases are listed in Table 7.

Table 6. Price Dispersion

| | Two-seller sessions | | | | | | Four-seller sessions | | | | | | p-val |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 1 | 2 | 3 | 4 | 5 | 6 | |
| Phase | | | | | | | | | | | | | |
| 1 | .356 | .351 | .377 | .325 | .407 | .301 | .553 | .545 | .525 | .501 | .435 | .513 | 0.001 |
| 2 | .646 | .744 | .579 | .726 | .613 | .593 | .850 | .850 | .748 | .693 | .775 | .777 | 0.004 |
| 3 | .345 | .310 | .363 | .336 | .311 | .306 | .489 | .513 | .488 | .512 | .473 | .521 | 0.001 |

Table 7. Change in Price Dispersion between Phases

| | Two-seller sessions | | | Four-seller sessions | | |
|---|---|---|---|---|---|---|
| | Phase 2 – 1 | Phase 3 – 2 | Phase 3 – 1 | Phase 2 – 1 | Phase 3 – 2 | Phase 3 – 1 |
| Session | | | | | | |
| 1 | 0.290 | –0.301 | –0.011 | 0.297 | –0.361 | –0.064 |
| 2 | 0.393 | –0.434 | –0.041 | 0.305 | –0.337 | –0.032 |
| 3 | 0.202 | –0.216 | –0.014 | 0.223 | –0.260 | –0.037 |
| 4 | 0.401 | –0.39 | 0.011 | 0.192 | –0.181 | 0.011 |
| 5 | 0.206 | –0.302 | –0.096 | 0.340 | –0.302 | 0.038 |
| 6 | 0.292 | –0.287 | 0.005 | 0.264 | –0.256 | 0.008 |
| p-value | 0.016 | 0.016 | 0.688 | 0.016 | 0.016 | 1.000 |

Once again, the model’s comparative static predictions are supported by our data. Across our treatments, the observed effects are statistically significant: price dispersion increases with the proportion of informed buyers, and with the number of sellers.

In summary, the theory makes clear predictions about the directions in which expected prices, expected minimum prices, and coefficients of variation should move in response to changes in our parameters. In all cases, our data support these comparative static predictions.

There are, however, discrepancies between theoretical and observed price distributions under each treatment. Figures 5-8 display the theoretical and empirical cumulative distribution functions for our four treatments (pooling all data from sessions with a given treatment).

[FIGURES 5-8 HERE]

Figures 5 and 6 illustrate the theoretical and empirical cumulative distributions in the Two-seller treatments. As the figures show, there is close to a stochastic dominance relationship between the empirical and theoretical distributions of prices. As a result, both the mean and median prices are higher in the empirical distribution than is predicted by the theory. (This pattern also holds for each session taken separately: inspection of Tables 1 and 2 show that the average price exceeds the theoretical mean in every phase of every session) Interestingly, the lower support of the empirical distribution is close to the theoretical prediction in Two-seller treatments. When the fraction of informed is one-half, fewer than 5% of price observations are below the theoretical lower support. When the fraction of informed consumers is 5/6ths, almost no prices occur below the theoretical lower support.

Figures 7 and 8 illustrate the theoretical and empirical cumulative distributions in the Four-seller treatments. The pattern of behavior in the Four-seller treatment differs from the Two-seller treatment in that there is no stochastic dominance relationship between the empirical and theoretical distributions. Indeed, when the fraction of informed consumers is one-half, the empirical distribution is approximately a mean-preserving spread of the theoretical distribution. In this case, the mean and median outcomes of the empirical distribution are quite close to their theoretical counterparts, but the variance of the empirical distribution is higher than that predicted by theory. (Again, this pattern holds in all sessions: see Table 6.) When 5/6ths of consumers are informed, the mean and median of the empirical distribution are higher than their theoretical counterparts. Unlike the Two-seller sessions, a higher fraction of prices lie below the theoretical lower support of the distribution. In the

Four-seller sessions, about 10% of price observations lie below the lower support of the theoretical distribution, compared with less than 5% for the Two-seller sessions.

An obvious question is whether these discrepancies are stable or decreasing over time. As we saw in Tables 3, 5, and 7, there was no significant change in average price, average minimum price, or the level of price dispersion from phase 1 to phase 3. Thus, there is little evidence that price distributions are converging to theoretical predictions.[11]

To summarize, while the comparative static predictions of the model are borne out by the data, the theoretical distribution is clearly not an *exact* description of behavior in our laboratory environment. Average prices are systematically higher than predicted in our Two-seller sessions, and in phase two of our Four-seller sessions. In phases one and three of our Four-seller sessions, average prices are close to the theoretical mean, but there is excessive price dispersion. Moreover, these discrepancies do not erode over the course of a session.

## 5. Discussion

In this Section, we explore two potential explanations for the discrepancy between the theoretical and empirical cumulative distributions of prices: risk aversion and bounded rationality in the form of a small fraction of "irrational" sellers. As we shall see, neither of these is very successful in reconciling the theory to the observed pricing behavior.

Our theoretical predictions are derived under the assumption that firms are risk-neutral. If subjects are risk averse, prices may deviate from the risk-neutral prediction, depending on how such risk attitudes are modeled. For example, it is straightforward to show that if all firms have identical risk-averse utility functions, the equilibrium distribution of

[11] We performed a similar test dividing Phase 2 into two halves and obtained similar results.

prices will stochastically dominate that derived under the assumption of risk-neutrality.[12] While this might explain the differences between the empirical and theoretical distributions in Figures 5 and 6, it is substantially at odds with Figure 7, where the empirical distribution actually *crosses* the theoretical at a price near the median. Put differently, if risk-aversion were a complete explanation, it would imply higher prices in the Four-seller sessions. In fact, average prices are very close to that predicted in that case.

A second explanation is based on the discussion in Dufwenberg and Gneezy (2000). They conducted experiments on Bertrand competition and found prices higher than predicted in three- and four-seller treatments, but not in two-seller treatments. They suggest an explanation based on 'noise traders'. If a small proportion of subjects choose higher prices than predicted, remaining subjects should also price higher than predicted. Once again, a key difficulty for this explanation is that it fails to account for the Four-seller sessions when $l$=1/2. There, prices are more dispersed, but not higher, than theoretically predicted.

Thus, some questions remain unanswered. In a recent paper, Roth (1996) discusses the interpretation of theory and experiment in the context of individual choice experiments. He argues that expected utility theory may be useful despite extensive evidence of anomalous behavior in experimental settings. He bases his argument on the view that theory may deliver useful *approximations* to observed behavior. This view can be easily extended to our strategic environment. At the outset we asked whether theory could successfully predict the direction in which market prices move in response to changes in market structure. To the extent that it does so, we regard our data as evidence of the usefulness of the theoretical model.

---

[12] Note that risk aversion does not affect the support of the equilibrium distribution. Let $p$ be given, and scale utility function $u(\ )$ so that $u(p(1-l)/n) = 0$, and $u((1-l)/n) = 1$. Let $u$ denote $u(p(l+(1-l)/n))$. Scale a more risk-averse utility function $v(\ )$ in the same way, so that $v = v(p(l+(1-l)/n)) < u$. The equilibrium distributions satisfy $(1-F_u(p))^{n-1}\, u = (1-F_v(p))^{n-1}\, v$, and since $v < u$ we have $F_u(p) > F_v(p)$ for all $p \in (p_0, 1)$.

## 6. Conclusion

Price comparison sites on the Internet have dramatically reduced the marginal cost of search for consumers seeking to buy products ranging from motherboards to Mother Goose. Empirical analysis of these markets shows that price dispersion is substantial and ubiquitous despite elasticity estimates suggesting that consumers tend to be quite price sensitive. One explanation for this persistent price dispersion is offered by clearinghouse models.

In this paper, we developed a simple clearinghouse model with clear comparative static implications, and used laboratory experiments to test these implications. Overall, we find strong support for the ability of clearinghouse models to predict the comparative static effects of changes in market structures.

In our experiments, we automated the demand behavior of two groups of consumers: 'informed' consumers who know the entire distribution of prices and buy at the lowest price on offer, and captive consumers who buy based on considerations other than price. When we increased the proportion of informed consumers, prices paid by both informed and captive customers decreased, as predicted. Likewise, when we increased the number of competing sellers, prices paid by informed consumers decreased, but the prices paid by captive consumers *increased*, again as predicted by the clearinghouse model.

The implications of changes in market structure we demonstrate have public policy implications. For example, consider the welfare consequences of alternative pro-Internet initiatives.[13] Initiatives to spur entry into e-commerce, such as sales tax exemption on Internet purchases, may have the perverse effect of disadvantaging individuals with limited Internet access and little chance to avail themselves of price comparison services. In contrast, the benefits from policies that subsidize high-speed connections in schools, rural areas, and in

[13] Some of these initiatives aim to reduce the digital divide, which refers to the idea that "information-poor" individuals - often low-income or poorly-educated – have limited access to information technology, while "information-rich" individuals - often high-income or well-educated – have much better access.

poorer neighborhoods, may be understated. Direct beneficiaries of these policies are individuals who get better access to price comparison services. At the same time, by increasing the proportion of “Internet-savvy” consumers, these policies encourage price competition among competing sellers, so that other consumers with good Internet access also benefit. Moreover, our results show that even those consumers who remain on the wrong side of the digital divide benefit from the positive externality on prices exerted by the growing fraction of “wired” consumers.

More broadly, our results have some general implications for understanding the effects of price competition. The word “competition” is ubiquitous in discussion of economic and current affairs, but its precise meaning is sometimes unclear. Often a competitive market is taken to be one with many firms; indeed various concentration indices are used as measures of competitiveness. Our results show that increased competition in this sense does not necessarily result in lower prices. An alternative view of competition is based on consumers’ ability to substitute away from high-priced firms. Our results suggest that increased competition in this sense does lead to lower prices.

Of course, our model and laboratory environments are simple, and abstract from many potentially important real-world features; thus these policy implications are merely suggestive. Further, the theoretical model does not exactly map to behavior in the laboratory. Specifically, we observe differences in the theoretical and empirical distribution of prices even though the predicted comparative static implications of the theory hold. Thus, further research on extensions of the model and subsequent empirical study seems warranted.

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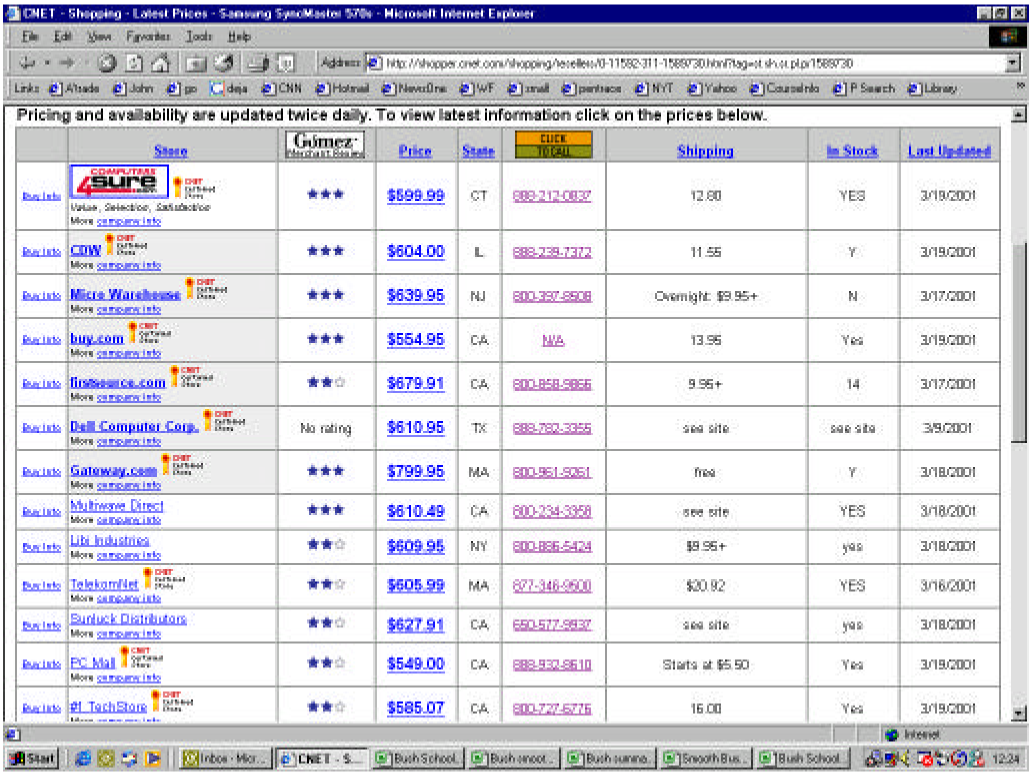
# Figures

## Figure 1: Screenshot of Price Comparison Listing at Shopper.com




## Figure 2. Subjects' Result Screen

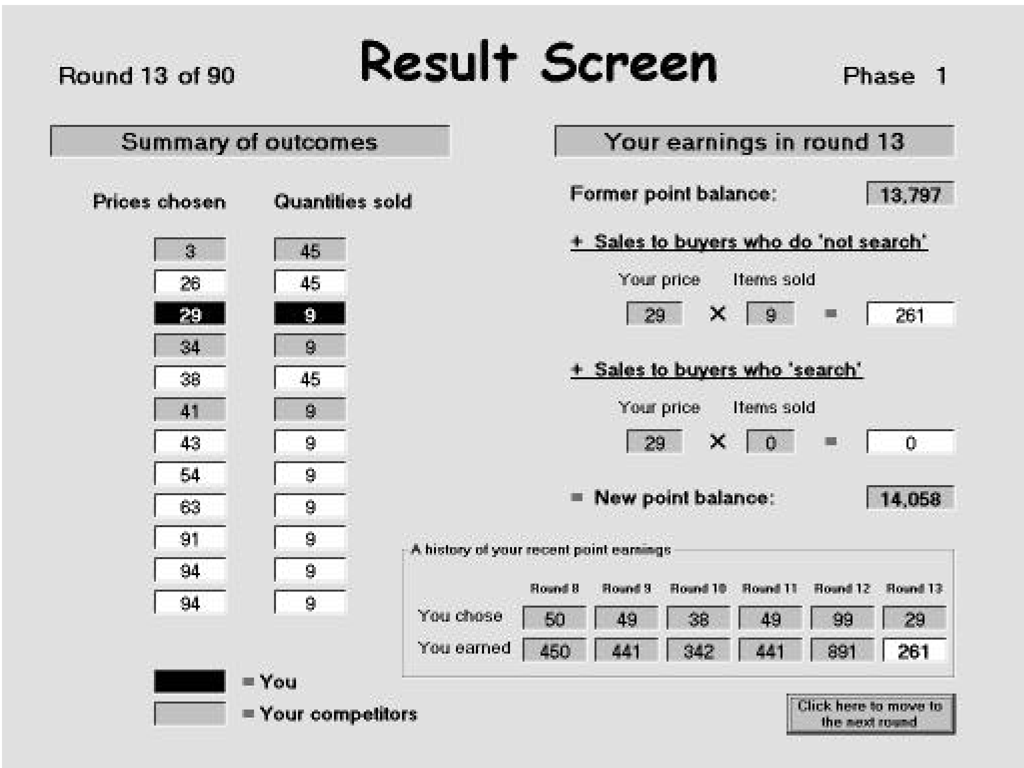


**Figure 3. Average Prices**

5-Period Moving Averages

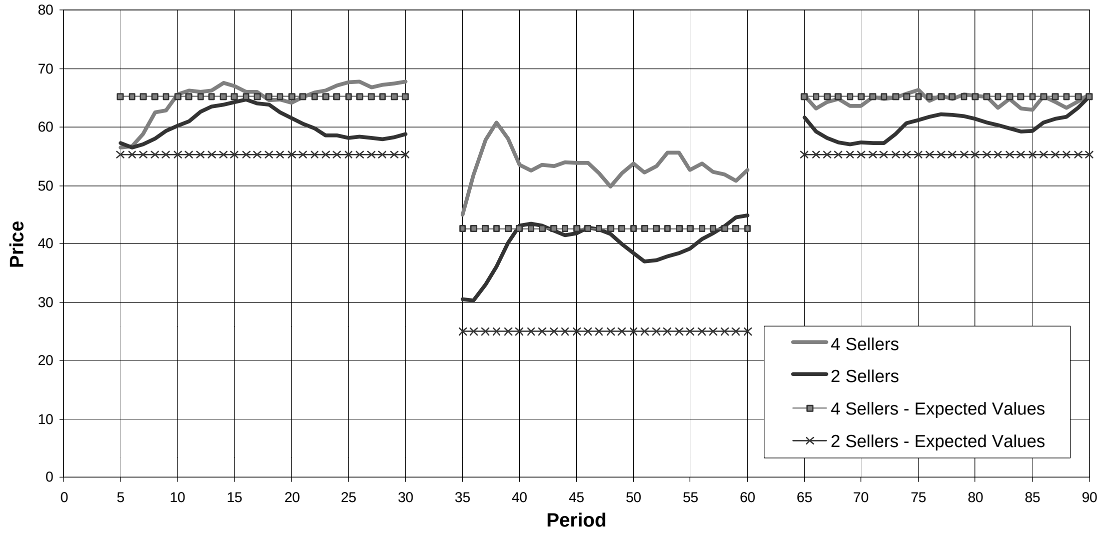



**Figure 4. Average Minimum Prices**

5-Period Moving Averages

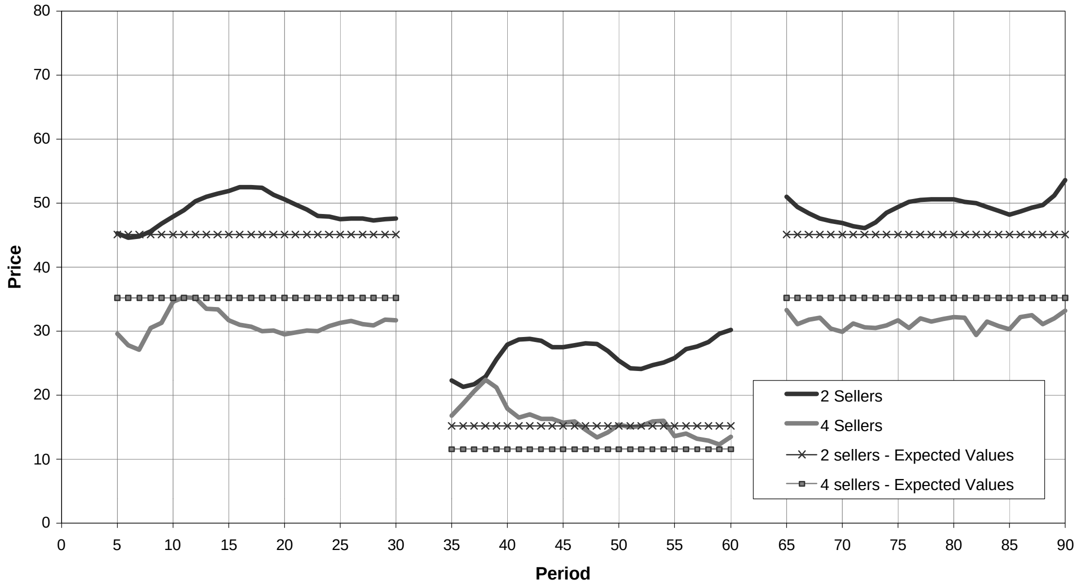


**Figure 5. Theoretical and Empirical Cumulative Distributions**

2 Sellers - Phases 1 and 3

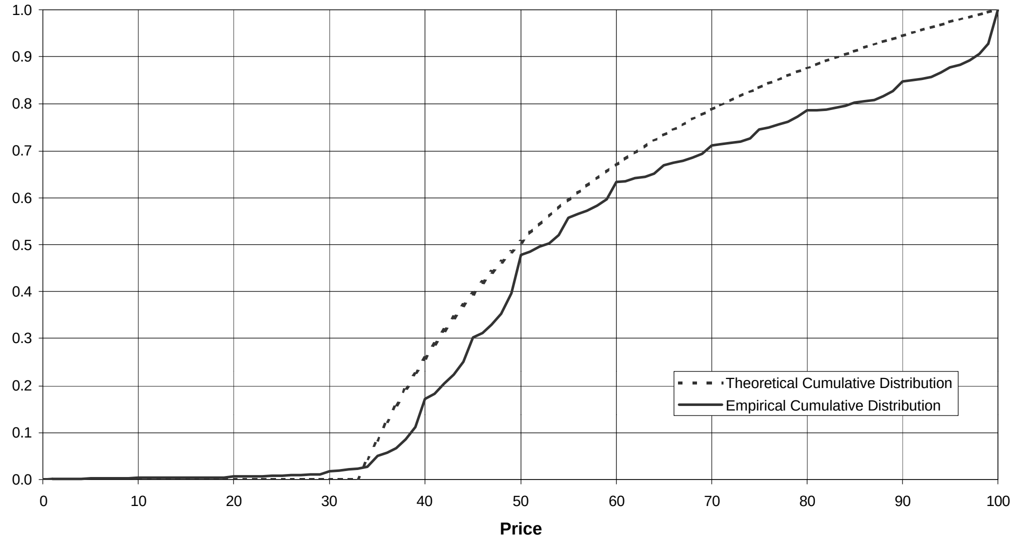



**Figure 6. Theoretical and Empirical Cumulative Distributions**

2 Sellers - Phase 2

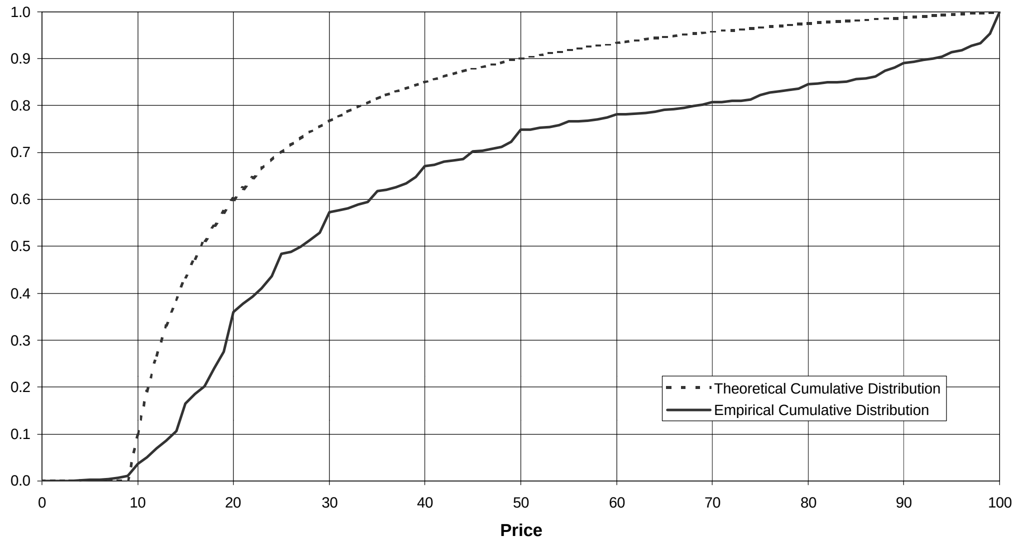


**Figure 7. Theoretical and Empirical Cumulative Distributions**

4 Sellers - Phases 1 and 3

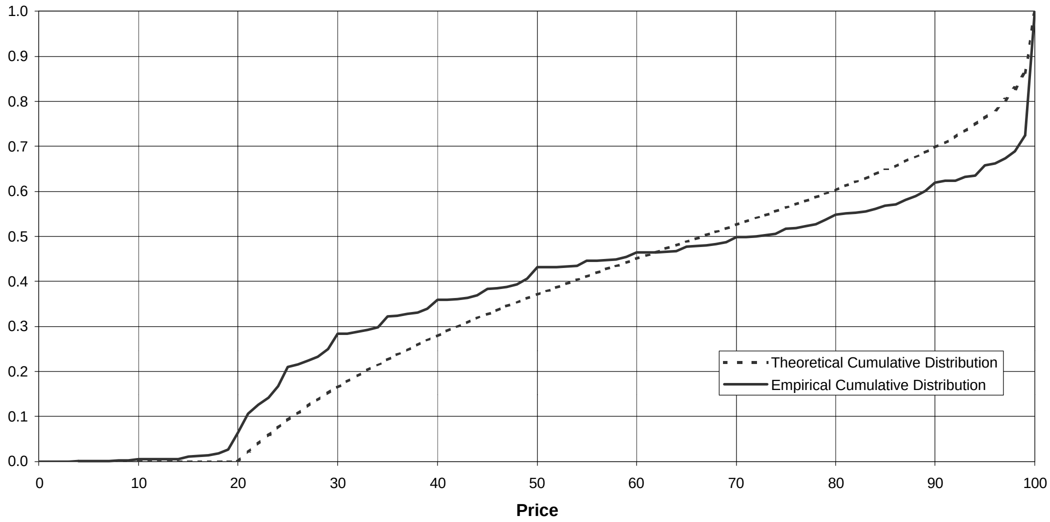
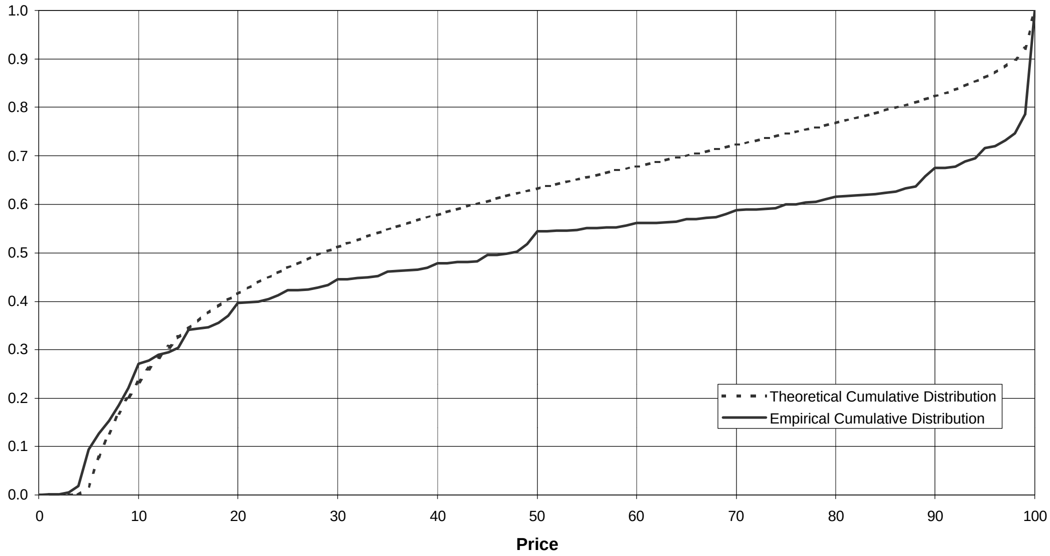



**Figure 8. Theoretical and Empirical Cumulative Distributions**

4 Sellers - Phase 2



## Appendix A. Proofs

**Proposition 1.** A symmetric equilibrium in the model entails all firms pricing according to the cumulative distribution $F(p) = 1 - \left( \frac{(1-l)(1-p)}{npl} \right)^{\frac{1}{n-1}}$ on the support [ $p_0$, 1], where

$p_0 = \frac{1-l}{nl + 1 - l}$ .

**Proof:** Deviating to a price lower than $p_0$ is not beneficial since pricing at $p_0$ generates a profit of $p_0(l + (1-l)/n)$, while pricing below this level nets no additional customers and so yields a lower profit. It is obvious that pricing above 1 is not a profitable deviation. Finally, since $F(1) = 1$, $F(p_0) = 0$, and $F(p)$ is increasing in $p$, $F$ is a well-defined cdf.

**Proposition 2.** As the fraction of informed consumers increases, the expected price paid by both informed and captive consumers decreases.

**Proof.** Differentiating the equilibrium distribution with respect to $l$ gives

$$\frac{dF(p)}{dl} = \frac{1}{n-1} \left( \frac{(1-l)(1-p)}{npl} \right)^{\frac{1}{n-1}} \frac{1}{l(1-l)} > 0.$$

Thus, the equilibrium distribution with smaller $l$ stochastically dominates that for larger $l$. As a result the expected price and the expected minimum price must both decrease as $l$ increases.

**Proposition 3.** As the number of firms increases, the expected price paid by informed consumers decreases and the expected price paid by captive consumers increases.

**Proof.** The industry expected profit is

$$\lambda\, E(p_{min}) + (1 - \lambda)\, E(p) = 1 - \lambda$$

where the right-hand side follows from the fact that all firms are indifferent between any equilibrium price and the monopoly price. Differentiating with respect to *n*, we obtain

$$l\,\frac{dE(p\min)}{dn} + (1-l)\frac{dE(p)}{dn} = 0,$$

or,

$$\frac{dE(p\min)}{dn} = -\left(\frac{1-l}{l}\right)\frac{dE(p)}{dn}.$$

Thus, the expected price paid by informed and captive consumers move in opposite directions with respect to *n*. It is also useful to note that this can be written as

$$\frac{dE(p)}{dn} = l\left(\frac{dE(p)}{dn} - \frac{dE(p\min)}{dn}\right). \quad [*]$$

Now, the expected price is given by

$$E(p) = \int_0^\infty (1-F(p))dp = p_0 + \int_{p_0}^1 \left(\frac{(1-p)(1-l)}{npl}\right)^{\frac{1}{n-1}} dp,$$

and so,

$$\frac{dE(p)}{dn} = \int_{p_0}^1 \frac{1}{n-1}(1-F(p))\left(-\frac{1}{n} - \ln(1-F(p))\right)dp.$$

The expected minimum price is

$$E(p_{\min}) = \int_0^\infty (1-F(p))^n\,dp = p_0 + \int_{p_0}^1 \left(\frac{(1-l)(1-p)}{npl}\right)^{\frac{n}{n-1}} dp$$

and so,

$$\frac{dE(p_{\min})}{dn} = \int_{p_0}^1 \frac{1}{n-1}(1-F(p))^n(-1-\ln(1-F(p)))dp.$$

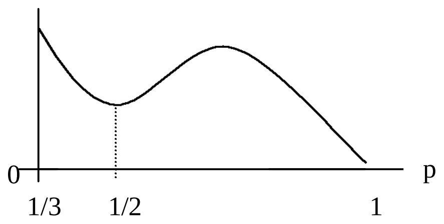
Substituting these into the right-hand side of [*] gives:

$$\frac{dE(p)}{dn} = l\int_{p_0}^1 \frac{1}{n-1}\left((1-F(p))\left(-\frac{1}{n} - \ln(1-F(p))\right) - (1-F(p))^n(-1-\ln(1-F(p)))\right)dp$$

or

$$\frac{dE(p)}{dn} = l\int_{p_0}^{1} h(p; l, n)dp$$

The function $h(\ )$ is sketched below for $l = 1/2$ , $n = 2$:




In fact, for all λ, $n$, the function $h(\ )$ has a similar shape: decreasing from $h(p_0) > 0$ to a local minimum at $p = 1 - l$, where $h(1 - l) > 0$, then increasing to a local maximum at $p = (1 - l)/(1 - l + n\, l \exp\{1/n - n\})$, then decreasing toward a limiting value of 0 as $p$ approaches 1. In particular we will show that $h(\ )$ is non-negative, and thus

$$\frac{dE(p)}{dn} > 0\ .$$

Note that $h$ is continuous with

$$\lim_{p\to 1} h(p; l, n) = 0$$

and

$$\frac{dh}{dp} = \left(\frac{n}{n-1}\right)\left((1-F(p))^{n-1} - \frac{1}{n}\right)\left(1 + \frac{1}{n} + \ln(1-F(p))\right)\frac{d(1-F(p))}{dp}$$

The first and last terms are positive and negative respectively. The other two terms are both decreasing in $p$. For small $p$ both middle terms are positive, and so $h(\ )$ is decreasing. For large $p$ both middle terms are negative, and so $h(\ )$ is decreasing. In an intermediate range, $1 - l < p < (1 - l)/(1 - l + n\, l \exp\{1/n - n\})$, the middle terms have opposite signs, and so $h(\ )$ is increasing. (The bounds are determined by the turning points where each of the middle terms evaluates to zero.) At $p = 1 - l$, $h(\ )$ has a local minimum and attains a value of

$$h(p; l, n)\Big|_{p=1-l} = \left(\frac{1}{n}\right)^{n/(n-1)} \frac{1}{n-1}\ln(n) > 0\ \ .$$

**Derivation of coefficient of variation.** The coefficient of variation is defined as:

$$coefficient\ of\ variation = \frac{\sqrt{Var(p)}}{E(p)}.$$

Since $F(p) = 1 - \left(\frac{(1-l)(1-p)}{npl}\right)^{\frac{1}{n-1}}$ on the support [$p_0$, 1], for $p \in$ [$p_0$, 1] the density is:

$$\begin{aligned} f(p) &= \frac{1}{n-1}\left(\frac{(1-l)(1-p)}{npl}\right)^{\frac{1}{n-1}-1} \frac{(1-l)}{nl}\frac{1}{p^2} \\ &= \frac{1}{p(1-p)}\frac{1}{n-1}\left(1-F(p)\right) \end{aligned}$$

and $f(p) = 0$ otherwise.

Thus,

$$E(p) - E(p^2) = \int_{p_0}^{1} p(1-p) f(p)dp = \frac{1}{n-1}\int_{p_0}^{1}\left(1-F(p)\right)dp = \frac{1}{n-1}\left(E(p) - p_0\right).$$

Rearranging and subtracting $(E(p))^2$ from each side gives:

$$E(p^2) - \left(E(p)\right)^2 = E(p) - \left(E(p)\right)^2 - \frac{1}{n-1}\left(E(p) - p_0\right)$$

or

$$Var(p) = E(p)\left(1 - E(p)\right) - \frac{1}{n-1}\left(E(p) - p_0\right).$$

Inserting this into the definition of the coefficient of variation, and substituting

$p_0 = \frac{1-l}{nl+1-l}$, gives the following expression:

$$coefficient\ of\ variation = \frac{\sqrt{E(p)\left(1-E(p)\right) - \frac{1}{n-1}\left(E(p) - \frac{1-l}{nl+1-l}\right)}}{E(p)}.$$

The coefficients of variation given in the text are calculated from this expression using the values given in Table 1.

## Appendix B. Pilot Sessions

Two pilot sessions were conducted using the same procedures as described in the text, except (1) subjects were mainly Ph.D. students, and (2) subjects completed a quiz to test whether they understood the instructions. All subjects completed this quiz correctly, and our view was that it merely lengthened the session: one of the pilot sessions exceeded ninety minutes. Rather than reduce the number of decision-making periods, we decided to eliminate the quiz for the twelve sessions reported in the text. The results from the pilot experiment are displayed below in Figures B1-B6, which were constructed in the same way as Figures 3-8.

**Figure B1. Average Prices (Pilot Data)**

5-Period Moving Averages

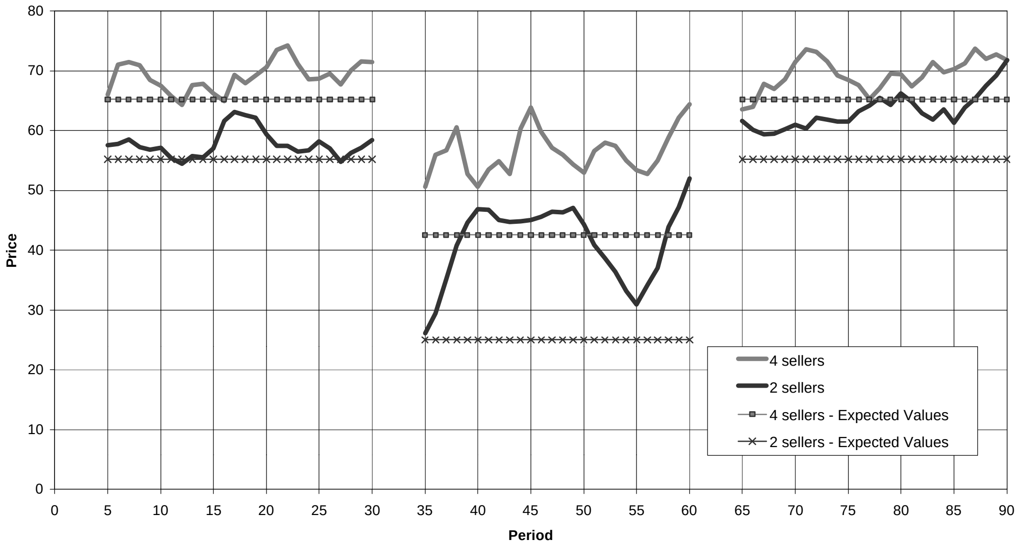



**Figure B2. Average Minimum Prices (Pilot Data)**

5-Period Moving Averages

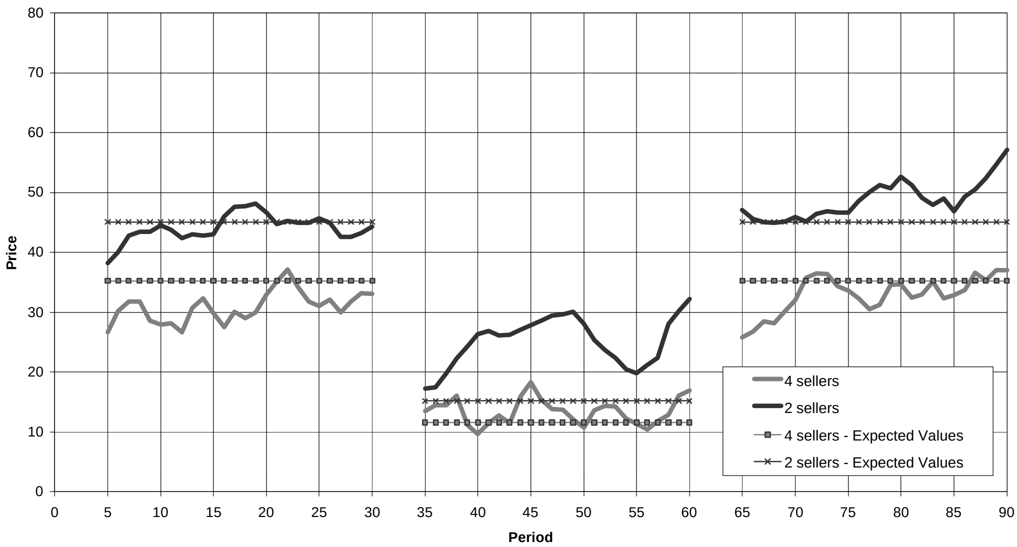


**Figure B3. Theoretical and Empirical Cumulative Distributions**

2 Sellers - Phases 1 and 3 (Pilot Data)

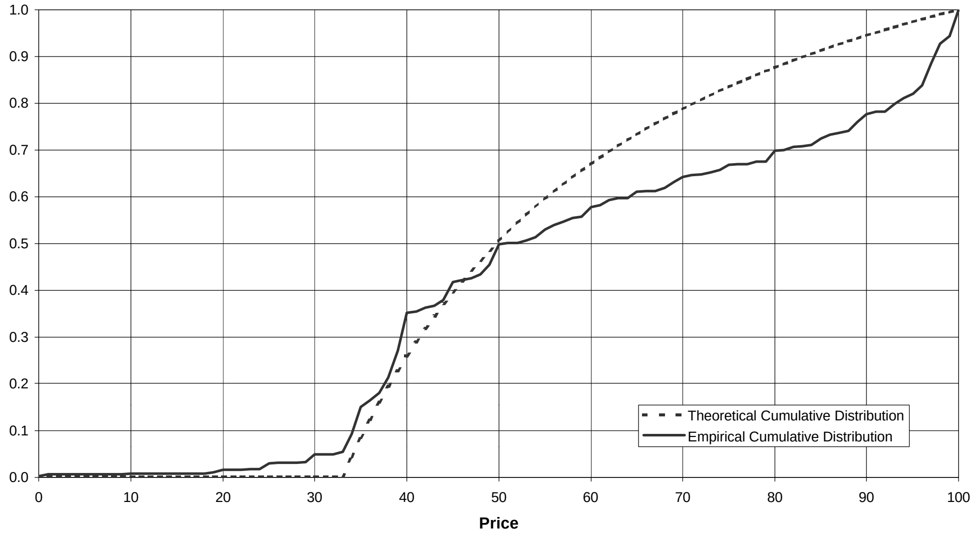



**Figure B4. Theoretical and Empirical Cumulative Distributions**

2 Sellers - Phase 2 (Pilot Data)

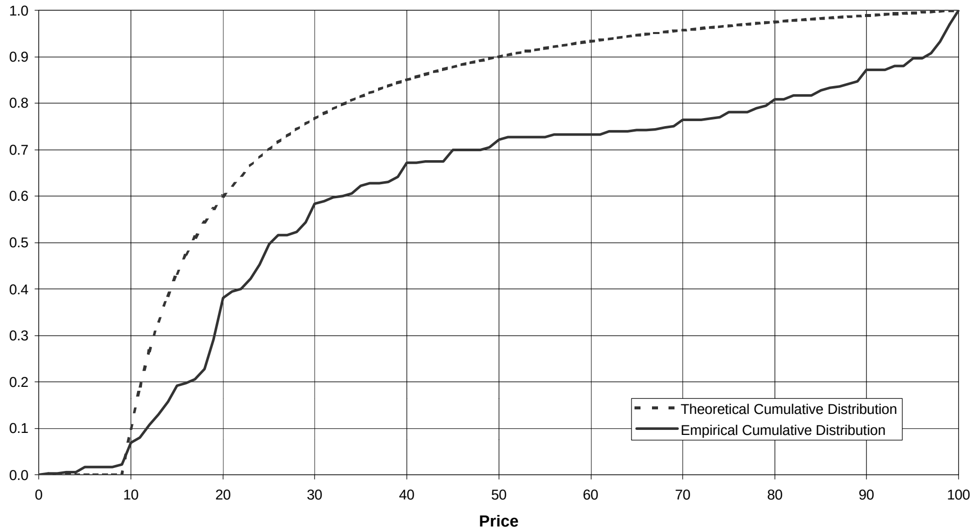


**Figure B5. Theoretical and Empirical Cumulative Distributions**

4 Sellers - Phases 1 and 3 (Pilot Data)

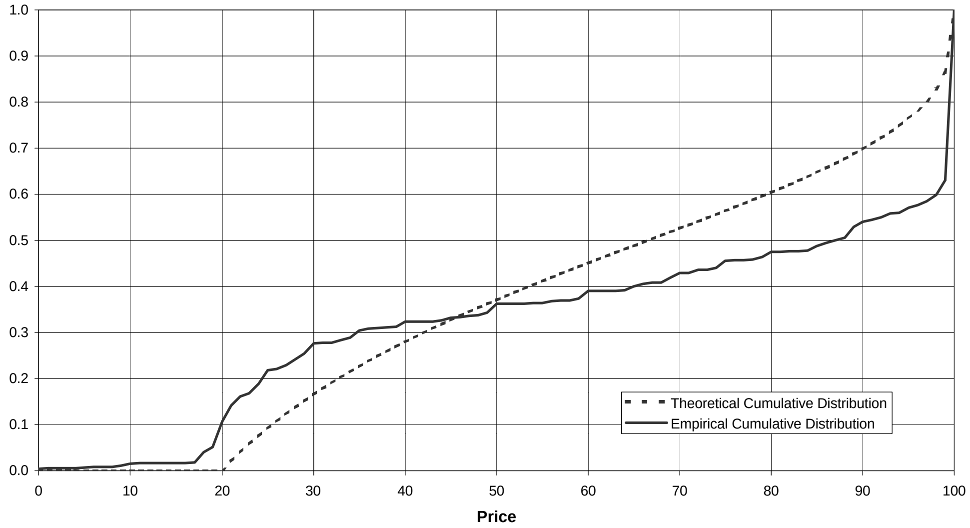
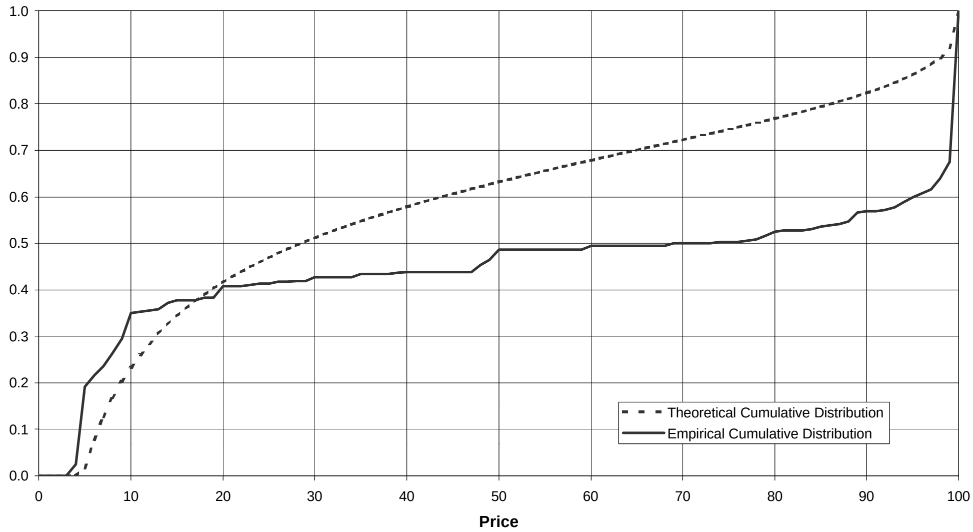



**Figure B6. Theoretical and Empirical Cumulative Distributions**

4 Sellers - Phase 2 (Pilot Data)



## Appendix C. Instructions

### General rules

This session is part of an experiment in the economics of decision making. If you follow the instructions carefully and make good decisions, you can earn a considerable amount of money. At the end of the session you will be paid, in private and in cash, a £3 participation fee plus an additional amount that will depend on your decisions.

There are twelve people in this room who are participating in this session. It is important that you do not talk to any of the other people in the room until the session is over.

The session will consist of 90 periods, in each of which you can earn points. At the end of the experiment you will be paid £3 plus an additional amount based on your total point earnings from all 90 periods. Points will be converted to cash using an exchange rate of 100 points = 1p. Notice that the more points you earn, the more cash you will receive at the end of the session.

### Description of a period

Each person in the room has been designated as a seller. In each period you will be competing with {one}[three] other seller[s], randomly selected from the people in this room. Your point earnings will depend on your decision and your competitor{'s}[s'] decision. Because sellers are randomly matched at the beginning of each period, the identity of your competitor[s] will change from period to period.

In every period, each seller decides what price to charge. You make your decision by entering a price (any whole number between 0 and 100) on your terminal. After all sellers have made their decisions, the computer will calculate the number of units sold by each seller as follows.

You and your competitor[s] will be selling to six computerized buyers. Each buyer will buy twelve units. Some of these buyers have been programmed to 'search': this type of buyer will buy twelve units from whoever chooses the lowest price out of you and your competitor[s]. (If there is a tie for the lowest price, the twelve units are evenly divided between {you and your competitor}[the tied competitors].) The rest of the computerized buyers have been programmed to 'not search': this type of buyer will buy {six}[three] units each from you and your competitor[s]. At the beginning of each period the number of buyers of each type will be displayed on your terminal.

Your point earnings from the period will be equal to the price you charge times the number of units you sell.

At the end of each period the prices charged by each seller will be displayed on your terminal, from lowest to highest. (You will be informed of the prices of all sellers in the session, not just the price[s] of your competitor[s] in that period. The rows corresponding to you and your competitor[s] will be highlighted.) Next to each price, the number of units sold by that seller will also be displayed. Your terminal will also display your point earnings for that period, your point earnings from the last five periods, and your accumulated point earnings from all periods.

**Differences between periods**

All periods are identical except that your competitor[s] will be changing from period to period, and the number of each type of buyer will be changing from phase to phase.

In Phase One, consisting of periods 1 to 30, there will be *three* computerized buyers programmed to search and *three* computerized buyers programmed to not search.

In Phase Two, consisting of periods 31 to 60, there will be *five* computerized buyers programmed to search and *one* computerized buyer programmed to not search. Otherwise, Phase Two is identical to Phase One.

In Phase Three, consisting of periods 61 to 90, there will be *three* computerized buyers programmed to search and *three* computerized buyers programmed to not search. That is, Phase Three is identical to Phase One.

**Starting the experiment**

We are now ready to begin the decision-making part of the session. Press the “start” button and follow the prompts on the screens. If you have any questions during the rest of the session raise your hand and a monitor will come to your desk and answer them in private.