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# Information and coordination frictions in experimental posted offer markets*

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**Abstract**

We experimentally investigate buyer and seller behavior in small markets with two kinds of frictions. First, a subset of buyers may have (severely) limited information about prices, and choose a seller at random. Second, sellers may not be able to serve all potential customers. Such capacity constraints can lead to coordination frictions where some sellers and buyers may not be able to trade. Theory predicts very different equilibrium outcomes when we vary the set-up along these two dimensions. In particular, it implies that a higher number of informed buyers will lead to lower prices when sellers do not face capacity constraints, while prices may actually increase if sellers are capacity constrained, as shown by Lester (2011). In the experiment, the differences between the constrained and non-constrained case are confirmed; prices fall when sellers are not capacity constrained but either do not fall by much or even increase when they are not. We find that prices are quite close to the predicted equilibrium values except in treatments where unconstrained sellers face a large fraction of informed buyers. However, introducing noise into the theoretical decision making process produces a pattern of deviations that fits well with the observed ones.

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# 1 Introduction

Many markets are small and are affected by information and coordination frictions. In labor markets, a worker has a limited number of suitable jobs to apply to, and in housing markets there is a limited number of properties a buyer can inspect on a given day. In a neighborhood there may be a limited number of grocery stores that a buyer can approach. Furthermore, in some markets sellers can serve all customers, like in a grocery store, whereas in other markets sellers are constrained in their capacity. In labor markets, for instance, usually one job is offered at a time by a firm, and the same is often the case in the the private segment of the housing maket and the market for used cars. When capacity is constrained, lack of coordination among applicants can result in some (suitable) job seekers not finding a job and some firms not finding a worker. That is, a coordination friction arises.

A substantial theoretical literature on the microstructures of such markets exists. It demonstrates that even small changes in the capacity of sellers or the informedness of buyers can impact profoundly on market outcomes.

In one strand of the literature, it is assumed that sellers can serve all buyers that show up, but that some buyers are uninformed about prices. Varian (1980), Burdett and Judd (1983), Stahl (1989), and Janssen and Moraga-González (2004) analyze markets where a fraction of buyers observe all the prices in the market. The remaining buyers are uninformed, and approach a seller at random. In the resulting equilibrium, sellers randomize over prices. As the fraction of informed buyers increases, the average price decreases, with the classic Bertrand equilibrium as the limiting case where price equals marginal cost.[1]

In another strand of the literature, starting with Montgomery (1991) and developed further by, among others, Burdett, Shi, and Wright (2001), it is assumed that all buyers observe all prices. However, sellers only have a limited number of goods for sale, which can be normalized to one. As buyers make independent decisions, a coordination friction emerges. Some sellers may get many and some sellers no customers. Where a queue forms, only one buyer will be served. Consequently market participants may end up without trading. The nature of the resulting equilibrium is in stark contrast to the equilibrium in which sellers are unconstrained. In the capacity constrained equilibrium, buyers randomize over which seller to approach, while sellers set a single (and equal) price. As buyers trade off the price with the probability of obtaining the good, the price elasticity of demand is relatively lower and the market price is strictly above the Bertrand price. If the buyer-seller ratio is high, sellers' may even set prices close to the buyers' willingness to pay.

In a recent paper, Lester (2011) introduces information frictions into a market setting with capacity constraints. He demonstrates that increasing the fraction of informed buyers may produce effects that differ dramatically from those obtained in a setting where sellers are unconstrained. While generally prices do not decrease by much they can even go up in some cases as the fraction of informed buyers increases. This counterintuitive result rests on the fact that a higher number of informed buyers stiffens the competition between informed buyers for the good. We refer to this as *Lester's paradox*.

In this paper we take all these cases within a unified setting to the lab. We run six treatments, with each treatment covering one particular market structure. In all treatments there are two sellers and three buyers with a unit demand. Sellers simultaneously advertise a price, and buyers subsequently and simultaneously decide which seller to approach. Across treatments we vary both the number of informed buyers from 1 to 3, and whether sellers can serve the whole market and

[1] An overview of this literature can be found in Baye, Morgan, and Scholten (2006).

sell up to three units or have only one unit in stock (the capacity constrained case).

Our findings are surprisingly consistent with predictions from theory. With capacity constrained sellers, the buyers' search behavior is remarkably close to what theory predicts, and prices are very close to the equilibrium predictions. In line with theory, prices are substantially higher when the buyers are capacity constrained than when they are not. Moreover, having more informed buyers leads to a substantial fall in prices when sellers are unconstrained but not when they are constrained, as predicted by theory. Finally, in the presence of capacity constraints, prices are predicted to increase when going from two to three informed buyers. Our data lend substantial support to Lester's paradox.

However, we also observe deviations from theory. In markets with no capacity constraints and two or three informed buyers prices are substantially higher than predicted, and the deviations are particularly strong in the pure Bertrand treatment. Strong deviations from equilibrium in Bertrand duopolies have frequently been observed in previous experiments.[2]

To better understand why the deviations vary in strength across treatments, we analyze buyer and seller behavior separately. We find that departures from Nash equilibria are mostly due to deviating seller behavior. We compare our data to the predictions arising from noisy price responses within a quantal response equilibrium (QRE). In QRE, the probability of an action is an increasing function of the expected payoff of taking that action. As noise vanishes the QRE converges to a Nash equilibrium. We fit the empirical price distributions in most of our treatments quite well with the one implied by QRE. Still, QRE is far off mark when all buyers are informed and sellers are capacity constrained. In order to better understand behavior we therefore investigate price setting when sellers believe they are facing a noisy opponent with positive probability, but - in contrast to the QRE - are reacting optimally and without noise to these beliefs. It turns out that markets with capacity constraints are much less sensitive to the particular form of such beliefs than are markets without constraints. We find that the sensitivity of expected seller profits to noisy deviations of the other seller closely mimicks the observed deviations in direction and magnitude.

Several experimental studies are of direct relevance to ours.[3] First, other papers have tested pricing behavior in a setting with capacity constraints and coordination frictions. Cason and Noussair (2007) explore the Burdett, Shi, and Wright (2001) equilibrium in a two-seller, three-buyer setting. They find prices quite close to equilibrium in the final periods of the experiment, and demonstrate that prices weakly converge towards a common value. Anbarci and Feltovich (2013) find no statistical difference between observed and theoretical prices in a similar setting. Further, in a concurrent and independent study, Anbarci and Feltovich (2014) examine treatments where sellers are capacity constrained and the fraction of informed buyers is varied. In contrast to us they fail to find support for Lester's paradox. Their interpration of this deviation from theory is based on fair pricing. Our design differs in important ways from theirs. In particular, we have more independent observations for each treatment and more than twice as many rounds within each observation. The latter difference might be important as behavior is converging slowly within

[2]We discuss the details of this literature in section 4.

[3]For a comparison of our results with studies that we replicate see Section 4 of the paper. The following is an incomplete list of experimental studies of related market environments. Anbarci and Feltovich (2013) examine the two-price model of Coles and Eeckhout (2000); Cason and Friedman (2003) examine the noisy sequential-search model of Burdett and Judd (1983); Cason and Datta (2006) examine a model due to Robert and Stahl (1993), in which sellers can advertise at a cost; Otto and Bolle (2011) and Abrams, Sefton, and Yavas (2000) examine markets in which there is bargaining after matching. There is also a large literature on posted offer markets in which buyers enter the market in a random order, see chapter 6-8 in Plott and Smith (2008).

the first 10 rounds of play.[4] A further difference is that our design also allows us to benchmark the impact of information frictions against the case where sellers do not face capacity constraints.

In our treatments with capacity constraints we test for equilibria in which buyer-coordination is not permitted. The study by Ochs (1990) analyzes how the degree of coordination depends on the matching protocol for agents and finds little support for coordination in high turnover markets. In our setting buyers are rematched every round. We find buyer behavior to be consistent with the play of mixed strategies.

Environments without capacity constraints such as the one by Varian (1980) have been tested by Morgan, Orzen, and Sefton (2006). Their results corroborate theory, i.e. more uninformed buyers create an upward pressure on prices. Furthermore, observed prices are consistent with the equilibrium price distributions in each treatment. Orzen (2008) argues that these results hinge on the stranger matching used, which prevent sellers from colluding effectively. Finally, the special case of Bertrand competition where all buyers are informed has been explored in Dufwenberg, Gneezy, Goeree, and Nagel (2007), Dufwenberg and Gneezy (2000) and in Abrams, Sefton, and Yavas (2000). Average posted prices amount to 20-40% of buyer valuation in the two-seller treatments of these experiments. In summary, almost all studies that have tested some of our treatments in isolation are in line with our findings.

The paper is organized as follows. In the next section we outline and explain the predictions from theory using a general environment for all six market structures. In section 3 we present our design and hypotheses. Section 4 presents our main results and then analyzes buyer and seller behavior. In the last part of section 4 we discuss more thoroughly how our results relate to results obtained in other experiments. Section 5 concludes.

## 2 Theoretical Predictions

In the following we describe the theoretical model on which our treatments are based. It encompasses the model of Lester (2011), the standard directed search model of Burdett, Shi, and Wright (2001), a version of Varian (1980),[5] and the classic Bertrand model as special cases.

The economy is populated by an integer number of $S \geq 2$ sellers and $B \geq 1$ buyers, all of which are risk neutral.[6] Buyers have a unit demand with a reservation price normalized to one. The model consists of two stages: First, sellers simultaneously set prices $p_s \in [0, 1]$. Firms commit to these prices ex-ante and no ex-post negotiations are allowed. In the second stage buyers simultaneously make buying decisions. A number $U \geq 0$ of uniformed buyers independently and randomly choose a seller, where each seller is visited with equal probability. Further, there are $N \geq 1$ (with $N+U = B$) informed buyers who can costlessly observe all prices offered in the market and choose at which seller to buy.

An important issue is the number of units each firm has for sale. We distinguish between two cases. In the first case, all firms are capacity constrained, and each firm has exactly one unit for sale. Hence, if two buyers show up, only one can be served. In the second case firms are not capacity constrained, and each firm has at least $B$ units for sale. In this case a seller can always serve all the customers that show up. Let $z$ be an index for capacity, $z = n$ indicates that firms

[4] This is in line with the finding of Anbarci and Feltovich (2014) that the contradictory result is alleviated when only the last 5 rounds are taken into account. See Cason and Noussair (2007) for related finding regarding convergence behavior. We discuss these and other design differences in more detail in section 4 below.

[5] In contrast to Varian (1980), we set costs equal to a constant normalized to zero.

[6] The constraints on the number of agents are only imposed to focus on the more interesting cases.

are not capacity constrained, $z = c$ indicates that they are.

The expected payoff of a seller $s$ is $\pi_s^z(p_s, p_{-s}) = \mu^z(p_s, p_{-s})p_s$, where $\mu^z(p_s, p_{-s})$ is the expected number of sales given by the number of units in stock ($z$), the own price and the prices of other sellers. The expected payoff of a buyer $i$ conditional on choosing a seller $s$ is $v_i^z(\theta_{-i}^s) = \eta^z(\theta_{-i}^s)(1 - p_s)$, where $\eta^z(\theta_{-i}^s)$ is the probability of getting the good at seller $s$ given that the other buyers go to this seller with probabilities $\theta_{-i}^s$. If the sellers are not capacity constrained, $z = n$, this probability is always 1. If the sellers are capacity constrained, the probability is typically strictly less than 1. If no seller is chosen the payoff is zero. It follows from the assumptions on uninformed buyers that $\theta_i^s = 1/S$ for all $i \in U$. We focus on sub-game perfect equilibria with symmetric (mixed) strategies. While this is the standard assumption in the theoretical literature, it is also justified in our experimental set-up since market participants are anonymous and new markets are formed randomly in each period, making coordination difficult.

**Equilibria with no Capacity Constraints** We first look at the case where there are at least some uninformed buyers, $U \geq 1$. The number of sales to uninformed customers is binomially distributed and thus equal to $U/S$ in expectation. The expected sales to informed agents only depend on whether or not the seller's price is lower than the other firms' prices. Thus $\mu^n(p_s, p_{-s}) = N + U/S$ if $p_s$ is the lowest price and $\mu^n(p_s, p_{-s}) = U/S$ otherwise.[7] One can show that the symmetric equilibrium entails a mixed strategy given by the c.d.f. $F(p)$ with support $p \in [p_0, 1]$.[8] It is convenient to determine the equilibrium strategy by looking at the indifference between the "rip-off" price of 1 and any other price in the support of $F(p)$: $\int \pi_s^n(p_s, p_{-s})dF(p_{-s}) = \int \pi_s^n(1, p_{-s})dF(p_{-s})$. This can be written as:

$$(U/S + N(1 - F(p_s))^{S-1})p_s = U/S \cdot 1 \tag{1}$$

The left-hand side shows the pay-off when setting a price $p_s$. Independent of the price, the seller will sell in expectation to $U/S$ uninformed sellers. If it sets the lowest price, it will in addition sell to $N$ informed sellers, and this happens with probability $(1 - F(p))^{S-1}$. The right hand side shows the expected pay-off when setting $p_s = 1$. Solving for $F(p)$ gives:

$$F(p) = 1 - \left(\frac{1-p}{p}\frac{U}{SN}\right)^{1/(S-1)} \quad \text{with } p \in [p_0, 1].$$

It is straightforward to verify that the lower bound of the support is given by $p_0 = \frac{U}{U+SN}$. Using the tail formula for the expected value, the expected price can be expressed as:

$$\begin{aligned} E[p] &= p_0 + \int_{p_0}^{1} (1 - F(p))dp \\ &= p_0 + \int_{p_0}^{1} \left(\frac{1-p}{p}\frac{U}{SN}\right)^{1/(S-1)} dp. \end{aligned} \tag{2}$$

Notice that this expected price is strictly decreasing in the number of informed buyers as a percentage of uninformed buyers, i.e. $N/U$. The CDF of the lowest price in the market is given

[7] It can be shown that $F(p)$ has no mass points so that ties are a measure zero event. The intuition is that if $F$ had a mass point at $p'$, the expected number of sales would increase discretely by lowering the price slightly below $p'$, hence advertising $p'$ cannot be optimal. See Varian (1980) for details.

[8] The supremum of the support has to be 1: if a firm knows with certainty that it will only attract uninformed buyers, the optimal price is the reservation value of uninformed buyers.

by $1-(1-F(p))^S$. By using the tail formula again it follows that the expected minimum price at which the informed buyers purchase the good is given by:

$$E[p_{\min}] = p_0 + \int_{p_0}^{1} \left( \frac{1-p}{p} \frac{U}{SN} \right)^{S/(S-1)} dp.$$

If there are no uninformed buyers, $U = 0$, we are in the classic Bertrand case, where $p_s = 0$ for all $s$ and all buyers choose any $\theta^s$ on the equilibrium path.

**Equilibrium with Capacity Constraints** With capacity constraints, sellers can only sell one unit of the good. If more than one buyer shows up, the seller randomizes between the buyers, leading to congestion effects on the buyer side. We begin with the case of $N = 1$ where the equilibria are similar to the ones with no capacity constraints. First, in the special case of $U = 0$, there are no congestion effects and the we are in the Bertrand case. Second, if $U > 0$ we can solve for the equilibrium c.d.f. for pricing strategies, $F(p)$, by using the indifference condition

$$[(1-F(p_s))^{S-1} + (1-(1-F(p_s))^{S-1})m]p_s = m \cdot 1,$$

where $m \equiv \mu^c(1, p_{-s}) = 1-(1-1/S)^U$ is the probability of having at least one uninformed buyer. The first term in the bracket is the probability of having the lowest price, in which case the good is sold with probability 1. The second term is the complementary probability of not having the lowest price, multiplied with the probability of getting an uninformed buyer. The right-hand side shows the expected pay-off when when $p_s = 1$. This yields the following distribution over prices:

$$F(p) = 1 - \left( \frac{m}{1-m} \frac{1-p}{p} \right)^{\frac{1}{S-1}}, \quad \text{with } p \in [p_0, 1],$$

where $p_0 = m$. The expected price is:

$$E[p] = p_0 + \left( \frac{m}{1-m} \right)^{1/(S-1)} \int_{p_0}^{1} \left( \frac{1-p}{p} \right)^{1/(S-1)} dp.$$

The expected minimum price is given by:

$$E[p_{\min}] = p_0 + \left( \frac{m}{1-m} \right)^{S/(S-1)} \int_{p_0}^{1} \left( \frac{1-p}{p} \right)^{S/(S-1)} dp.$$

If $N > 1$ there is an important additional trade-off for informed buyers. On the one hand buyers prefer to purchase the cheapest good, on the other hand the cheapest offer will attract the highest number of informed buyers. The probability of receiving the good if in total $k$ uniformed and $j$ other informed buyers show up is $1/j+k+1$. For an informed buyer $i$ who has chosen to buy at a seller $s$ the probability of being served is thus given by[9]:

$$\eta^c(\theta^s_{-i}) = \sum_{j=0}^{N-1} \sum_{k=0}^{U} \frac{(N-1)!}{j!(N-1-j)!} (\theta^s_{-i})^j (1-\theta^s_{-i})^{N-1-j} \frac{U!}{k!(U-k)!} (1/S)^k (1-1/S)^{U-k} \frac{1}{j+k+1}. \tag{3}$$

[9]This follows from the binomial distribution. For more details about this and the remainder of the paragraph see Lester (2011).

As is common in directed search models, we focus on symmetric mixed buyer strategies. In equilibrium informed buyers have to be indifferent between sellers. That is, the randomization over sellers by informed buyers must be such that all informed buyers get the same expected value at any seller they approach with a positive probability. That is, $v_i^c(\theta_{-i}^{s'}) = v_i^c(\theta_{-i}^{s''})$ for any $s', s'' \in S$ such that $\theta_i^s > 0$, $s = s', s''$. Together with the requirement $\sum_s \theta^s = 1$ this gives a system of equations that implicitly determines the functions $\{\theta^s(p_s, p_{-s})\}_{s\in S}$, which sellers use in the first stage to forecast buyer behavior.

Next, the probability that a seller $s$ gets at least one buyer is given by:

$$\mu^c(p_s, p_{-s}) = 1 - (1 - \theta^s(p_s, p_{-s}))^N (1 - 1/S)^U.$$

In general, there can be equilibria with pure or mixed strategies on the sellers' side. In particular, if there are relatively many uninformed buyers there is an incentive to deviate from a pure strategy equilibrium by charging the highest price of 1, rendering such an equilibrium impossible. However, for the parameter constellations of our treatments, there will be only symmetric equilibria where sellers play pure strategies. These pure strategies can be determined by solving seller $s$' profit maximization problem

$$\max_{p_s} \mu^c(p_s, p^*_{-s}) p_s$$

given that all the other firms charge the equilibrium price $p^*$. The seller forecasts the buying probability $\theta^s(p_s, p^*)$ from the indifference condition of the buyers: $\eta^c(\theta^s)(1-p_s) = \eta^c((1-\theta^s)/(S-1))(1-p^*)$. Substituting the conditions of a symmetric equilibrium, i.e. $p_s = p^*$ and $\theta^s(p^*, p^*) = 1/S$, into the first order condition of the firm's problem, one can solve out the (unique) equilibrium price:

$$p^* = M/[M + (1 - \mu(p^*, p^*))\eta(1/S)\{N(B-1)/(S(N-1))\}], \tag{4}$$

where $M \equiv \mu(p^*, p^*)(\eta(1/S) - (1 - 1/S)^{B-1})$ and $\mu(p^*, p^*)$ reduces to $1 - (1 - 1/S)^{N+U}$. For this to be a pure strategy equilibrium it must hold that charging the rip-off price of $p = 1$ is not a profitable deviation, i.e.: $\mu(p^*, p^*)p^* \geq \mu(1, p^*) \cdot 1$. This condition is satisfied for the parameters of our treatments. In stark contrast to the case of no capacity constraints given in (2), expression (4) implies an equilibrium price that can be increasing in the number of informed buyers given $S$ and $B$ (Lester's paradox).

To gain intuition as to why more informed buyers' may lead to a higher price, we divide the effects of more informed buyers into two. First we have a rip-off effect, fewer uninformed buyers imply that there are fewer customers that are insensitive to prices, and this reduces the incentives to charge a high price. In contrast to the standard case, the presence of capacity constraints implies an additional competition effect that goes in opposite direction. A higher number of informed buyers leads to stronger competition for sellers with a low price. As buyers not only care about the price but also about the probability of getting the good, higher competition makes low price sellers less attractive. More specifically, the indifference condition for buyers entails a trade-off between the probability of approaching a seller ($\theta^s$) and the price ($p_s$). When a firm sets its price to maximize profits it anticipates that a lower price leads to a higher chance of getting customers. How strongly demand responds to price changes depends on the number of informed buyers. The price elasticity will be lower if there is more competition on the buyer side, because congestion decreases the attractiveness of a low price seller. Thus, the competition effect tends to increase prices when the number of informed buyers goes up.

## 3 Parameters and Procedures

We use a 2×3 design to investigate behavior in experimental markets with $S = 2$ sellers and $B = 3$ buyers. The experiment consists of a class of markets that differ along two dimensions. The first dimension is whether sellers are capacity constrained or not, i.e. $z = c$ or $z = n$. The second dimension is how many of the three buyers are informed, $N = 1$, $N = 2$, and $N = 3$. Uninformed buyers are strategic dummies, whose actions are restricted to randomize over sellers. In the experiment uninformed buyers were computer programs flipping fair coins to determine where to purchase. All informed buyers and all sellers were human subjects.

In all treatments prices and payoffs were measured in experimental currency units (ECUs). Buyers valuations were set to 100 ECU, and sellers marginal costs to 0 ECU.

In each treatment, one market constellation is played. Each treatment consists of five blocks, and each block consists of three markets. All treatments lasted 50 periods, and each period corresponded to a two-stage game. Subjects were randomly allocated a label prior to the start of trading, and kept this label for the 50 periods of play. Buyers were labeled "Blue", "Red" and "Green", and sellers were labeled "Circle" and "Square". Subjects were randomly assigned to the three markets within each block at the start of each period in a session, however in such a way that all labels were present in all markets. No subject was ever allocated across blocks, and no information on behavior in other blocks was conveyed to subjects. Unique subjects were used in all blocks. Thus, observations at the block-level are independent.[10]

A total of 360 subjects were used for the experiment, and a total of 18000 individual decisions (by humans) were collected. Some sessions used students from the University of Konstanz, Germany, other sessions used students from the Norwegian Business School in Oslo, Norway. As we show below, there are no significant differences between blocks collected in Oslo and Konstanz. We therefore pool data from the two locations. Data were collected between November 2012 and February 2014. Table 1 provides an overview of the experiment. We denote treatments by $T_N^z$.

Table 1: Treatments and blocks

| | # of blocks | |
|---|---|---|
| Treatment | Oslo | Konstanz |
| $T_1^n$ | 5 | 0 |
| $T_2^n$ | 2 | 3 |
| $T_3^n$ | 5 | 0 |
| $T_1^c$ | 5 | 0 |
| $T_2^c$ | 2 | 3 |
| $T_3^c$ | 2 | 3 |

[10]Concerns that heterogenous buyers can lead to a coordination equilibrium have been raised in the theoretical literature on directed search (Coles and Eeckhout (2000)). In our environment buyers have access to a minimal identification technology, since they play in fixed labels. We find that this is not sufficient to promote buyer coordination in treatments $T_1^c$ to $T_3^c$: empirical visit probabilities of informed buyers match the theoretical visit probabilities of such buyers very closely (see section 4 below). Another concern is that sellers may use labels (and set prices with decimals) to facilitate collusion on prices above equilibrium. However, only in treatments $T_2^n$ and $T_3^n$ prices are substantially above equilibrium levels. Moreover, in $T_3^n$ the average price relative to the buyer valuation is very close to ones found in the other studies discussed and where no fixed labels where used. Instead, our interpretation of these deviations is built on noisy best responses, which we discuss in section 4 below. About collusion and coordination in posted offer markets see also Davis and Holt (1996), Ochs (1990), and Orzen (2008).

Subjects were recruited online using the ORSEE system (Greiner (2004)). The experiment was programmed in z-Tree (Fischbacher (2007)), and was contextualized as a market, using terms such as "sellers", "buyers", "prices" and "queues". Subjects were randomly allocated to numbered cubicles on entering the lab (to break up social groups). After being seated, each subject was issued written instructions and these were read aloud by the administrator of the experiment (to achieve public knowledge of the rules). There were no test periods, and no control questions to check understanding. Sellers were allowed to post prices with two decimals. Strict anonymity was preserved throughout. Each period consisted of a posting stage, and a purchase stage. Sellers posted prices simultaneously, human buyers then observed the prices posted and simultaneously chose one seller to go to. In treatments with capacity constraints, if a queue formed at a seller the transacting buyer (human or computer program) was drawn with a uniform probability from the queue. At the end of each period all subjects got feedback on the whole history of posted prices, queues at each seller, transactions in the market he or she was operating, as well as own profit.

After period 50 was concluded, accumulated ECUs were converted to NOK or Euros (depending on the location) at a pre-announced exchange rate, and subjects were paid privately on leaving the lab. On average a session took 70 minutes. In the Oslo treatments average earnings were 54 US dollars. In the Bertrand treatment ($T_3^n$) all subjects got a (pre-announced) flat fee of 27 US dollars plus whatever they earned in the session. This was done in order to avoid sellers not earning money in the experiment. In all other treatments subjects got what they earned plus a show up fee. Earnings in the Konstanz treatments were adjusted to give the same consumer purchasing power as the Oslo treatments.

Table 2 provides the expected prices, and the cumulative price distributions and the support where appropriate, following from theory laid out in Section 2.[11] Note that when firms are capacity constrained (c), the price is 6 units lower when two buyers are informed as than if all three buyers are informed (Lester's paradox).

Table 2: Theoretical predictions: Expectation, support and distribution of prices

| $z$ | $N$ = 1 | $N$ = 2 | $N$ = 3 |
|---|---|---|---|
| $n$ | $E(p) = 69.3$<br>$p \in [50, 100]$<br>$F(p) = \left(\frac{2p-100}{p}\right)$<br>$E(p_T) = 66.7$ | $E(p) = 40.2$<br>$p \in [20, 100]$<br>$F(p) = \left(\frac{5p-100}{4p}\right)$<br>$E(p_T) = 33.3$ | $E(p) = 0.0$<br>$E(p_T) = 0.0$ |
| $c$ | $E(p) = 86.3$<br>$p \in [75, 100]$<br>$F(p) = \left(\frac{4p-300}{p}\right)$<br>$E(p_T) = 85.7$ | $E(p) = 66.7$<br>$E(p_T) = 66.7$ | $E(p) = 72.7$<br>$E(p_T) = 72.7$ |

*p: posted prices; $p_T$: transaction prices*

Standard theory produces three price distributions and three point prices. Expected prices are higher with capacity constrained sellers, for each level of informed buyers. If sellers are unconstrained prices fall monotonically as more buyers become informed. As noted, this is not the case if sellers are constrained. Where equilibrium prices are distributions, theory places precise bounds

[11] In table 2 and in the following the prices given in Section 2 are scaled by factor 100 as this is the price range in terms of ECU used in the experiments. For the derivation of transaction prices see Appendix 6.1.

on the price support and predicts a particular shape of the cumulative price distribution. When prices are dispersed in equilibrium expected transaction prices are below expected posted prices, as informed buyers in these cases always go for the lowest price offered.

## 4 Results

**Market behavior** Figure 1 provides a treatment-by-treatment comparison of observed prices and their theoretical counterparts, averaged over all periods and all blocks.

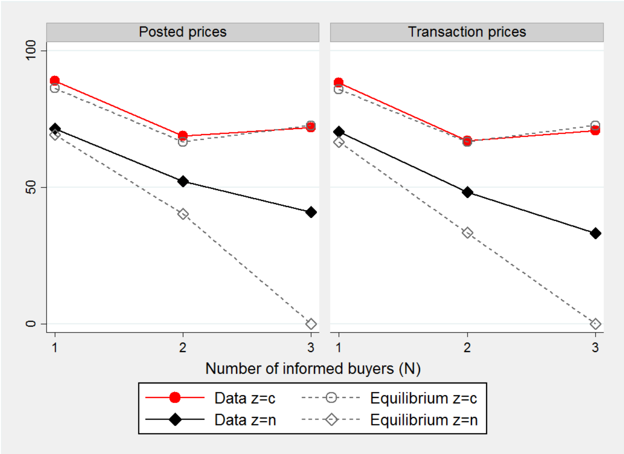


Figure 1: Posted prices and transaction prices for each treatment. Average posted prices (transaction prices) for treatments $T_1^n$ to $T_3^c$ are 71.4 (68.8), 52.3 (44.3), 41.6 (32.2), 89.1 (88.0), 68.9 (66.5), 71.9 (70.3), respectively.

As can be seen, average posted prices are remarkably close to the theoretical equilibrium values in treatments $T_1^n$ , $T_1^c$, $T_2^c$, and $T_3^c$, while they deviate substantially in treatments $T_2^n$ and, especially $T_3^n$, the market with Bertrand competition. Transaction prices are similarly close to their respective equilibrium values, and also exhibit the strongest deviations for treatments $T_2^n$ and $T_3^n$.[12] For both posted and transacted prices the predicted patterns are clearly visible: prices with capacity constrained sellers are always above prices with unconstrained sellers. Further, prices decrease with the number of informed buyers when there are no capacity constraints and either slightly fall or slightly increase otherwise. We summarize this in the following informal result.

**Result 1 (Average prices: data and theory)** *Average posted prices are very close to the theoretical expected prices in treatments $T_1^n$, $T_1^c$, $T_2^c$, and $T_3^c$, while they deviate substantially in treatments $T_2^n$ and $T_3^n$. Transaction prices are similarly close and exhibit the same pattern of deviations.*

We test differences between treatments with one-sided Wilcoxon rank sum (WRS) tests using blocks as units of observation.

For posted prices the differences between treatment $T_1^n$ and $T_1^c$ (W=-2.402; p=.008), $T_2^n$ and $T_2^c$ (W=-2.611;p=.005), and $T_3^n$ and $T_3^c$ (W=-2.611; p=.005) are all significant at the 1% level.

[12]In $T_2^n$ the deviation in percent of the theoretical price is 30.1 for posted prices and 33.0 for transaction prices. In $T_3^n$ this measure is not defined. For the other four treatments deviations in percent of theoretical posted prices are between 3.3 and 1.1, and between 3.3 and 0.3 for transaction prices.

Furthermore, posted prices decrease when going from treatment $T_1^n$ to $T_2^n$ (W=2.611; p=.005); and when going from $T_2^n$ to $T_3^n$ (W=2.193; p=.014). These price decreases are significant at the 5% level or better. WRS tests also reveal that posted prices decrease significantly from treatment $T_1^c$ to $T_2^c$ (W=2.611; p=0.005). The increase in posted prices from treatment $T_2^c$ to $T_3^c$, however, is not significant at conventional levels (W=-1.149; p=0.125). Nonetheless it is close to being significant at the 10% level, and we find this quite remarkable, considering that theory predicts an increase in prices between $T_2^c$ and $T_3^c$ by a measly 6 ECUs, and that the WRS test uses only five observations in each treatment.

**Result 2 (Treatment differences for posted prices)** *The differences in posted prices between the treatments with and without capacity constraints for a given number of informed buyers are all significant. Furthermore, the decrease in posted prices when going from treatment $T_1^n$ to $T_2^n$, from $T_2^n$ to $T_3^n$, and from $T_1^c$ to $T_2^c$ are significant.*

Our results become stronger for transaction prices. The differences between treatment $T_1^n$ and $T_1^c$ (W=-2.402; p=.008), $T_2^n$ and $T_2^c$ (W=-2.611; p=.005), and $T_3^n$ and $T_3^c$ (W=-2.611; p=.005) are all significant at the 1% percent level. Transaction prices also decrease when going from treatment $T_1^n$ to $T_2^n$ (W=2.611; p=.005), and when going from $T_2^n$ to $T_3^n$ (W=2.402; p=.008). These reductions are significant at the 1% level or better. WRS tests also show that transaction prices decrease significantly from treatment $T_1^c$ to $T_2^c$ (W=2.611; p=.005). Finally, the increase in transaction prices from treatment $T_2^c$ to $T_3^c$ is now significant at the 10% level, and almost significant at the 5% level (W=-1.567; p=.059). [13]

**Result 3 (Treatment differences for transaction prices)** *The differences in transaction prices between the treatments with and without capacity constraints for a given number of informed buyers are all significant. Transaction prices also decrease significantly when going from treatment $T_1^n$ to $T_2^n$, from $T_2^n$ to $T_3^n$, and from $T_1^c$ to $T_2^c$, while transaction prices increase significantly when going from $T_2^c$ to $T_3^c$.*

Table 3 reports regressions of prices on treatment dummies. Standard errors are clustered on individual sellers to correct for heteroscedasticity. In regressions labeled $PP$ the dependent is the posted price, while in regressions labeled $TP$ the dependent is the transaction price.

[13] With one exception, results are unchanged if the WSR-tests use only data from periods 11-48 (after learning has taken place and before the onset of endgame effects). The one exception is that the drop in posted prices from $T_2^n$ to $T_3^n$ is no longer significant in a one sided test when data are restricted in this way (W=0.940; p=.174).

Table 3: Treatment regressions.

| | *PP I* | | *PP II* | | *TP I* | | *TP II* | |
|---|---|---|---|---|---|---|---|---|
| Constant | 40.9 | *** | 37.4 | *** | 33.6 | *** | 29.2 | *** |
| | (2.93) | | (2.24) | | (2.42) | | (1.78) | |
| $T_1^n$ | 28.6 | *** | 30.4 | *** | 34.7 | *** | 37.2 | *** |
| | (3.97) | | (2.94) | | (3.62) | | (2.67) | |
| $T_2^n$ | 9.5 | ** | 11.3 | *** | 12.7 | *** | 15.1 | *** |
| | (3.95) | | (3.18) | | (3.42) | | (2.93) | |
| $T_1^c$ | 42.7 | *** | 48.1 | *** | 48.7 | *** | 55.0 | *** |
| | (3.52) | | (2.51) | | (3.14) | | (2.19) | |
| $T_2^c$ | 24.8 | *** | 28.0 | *** | 30.1 | *** | 33.9 | *** |
| | (3.85) | | (2.59) | | (3.22) | | (2.24) | |
| $T_3^c$ | 25.1 | *** | 30.9 | *** | 30.1 | *** | 37.5 | *** |
| | (3.93) | | (2.51) | | (3.42) | | (2.15) | |
| $T_1^n$·Period | 0.05 | | | | 0.08 | | | |
| | (0.13) | | | | (0.13) | | | |
| $T_2^n$·Period | 0.07 | | | | 0.10 | | | |
| | (0.14) | | | | (0.13) | | | |
| $T_1^c$·Period | 0.19 | | | | 0.22 | | | |
| | (0.12) | | | | (0.12) | | | |
| $T_2^c$·Period | 0.14 | | | | 0.16 | | | |
| | (0.12) | | | | (0.11) | | | |
| $T_3^c$·Period | 0.24 | ** | | | 0.28 | ** | | |
| | (0.12) | | | | (0.12) | | | |
| Period | 0.03 | | 0.14 | *** | 0.01 | | 0.16 | *** |
| | (0.11) | | (0.03) | | (0.11) | | (0.03) | |
| Lab | -1.5 | | | | -1.8 | | | |
| | (1.87) | | | | (1.69) | | | |
| N | 9000 | | 9000 | | 7095 | | 7095 | |
| $R^2$ | 0.45 | | 0.43 | | 0.52 | | 0.52 | |
| F-stat | 50.8 | *** | 91.4 | *** | 80.4 | *** | 144.5 | *** |

*Dependent: Posted prices (PP) or Transaction prices (TP) for all periods. Coefficients (robust standard errors clustered on sellers). Reference category:* $T_3^n$ *(Bertrand competition). Significant at level *** 1%; ** 5%; *10 %.*

Specifications *PP I* and *TP I* are saturated models in which treatment dummies are interacted with periods. We also include a dummy for the lab, that takes the value 1 for Konstanz and 0 for Oslo. Only one of the multiplicative terms is significantly different from zero. The lab dummy does not have a significant effect on prices. In specifications *PP II* and *TP II* we drop the multiplicative terms and the lab dummy. The trend variable for periods is positive and significantly different from zero, albeit of moderate size. The regressions are highly robust for exclusion of periods.[14]

T-tests for differences in regression coefficients confirm the results from the WRS-tests. It is noteworthy that the t-test for differences between treatments $T_2^c$ and $T_3^c$ rejects the null hypothesis

[14] In particular results are practically unchanged if periods 49 and 50 are excluded, or if periods 1-10 and 49-50 are excluded. Arguments for dropping the last couple of periods in experiments with finite and publicly known horizons are provided by Cason and Noussair (2007). Footnote 7 in that paper provides further references.

that the coefficient of $T_2^c$ is less than or equal to that of $T_3^c$ with a $p$-value of 0.061 for posted prices, and with a $p$-value of 0.028 for transaction prices. Hence the null hypothesis that prices do not increase is rejected at a 10% significance level, and is close to being rejected at the 5% significance level using posted prices, while it is comfortably rejected at the 5% significance level using transaction prices. Thus, regressing prices on treatment dummies and a time trend lends further support to Lester's paradox.[15] We summarize our findings in regard to this price increase in the following result.

**Result 4 (Lester's paradox)** *Both posted prices and transaction prices increase significantly from treatment $T_2^c$ to $T_3^c$. The effect with respect to transaction prices is statistically less uncertain than the effect with respect to posted prices.*

The regression also shows that transaction prices are below posted prices in all treatments. For treatments where the optimal strategy prescribes mixing (i.e. $T_1^n$, $T_2^n$, $T_1^c$) this is according to theory, as informed buyers should take the lowest offer and not the average one. In the other treatments theory implies that transaction prices are identical to posted prices, as each seller should offer the same price in equilibrium. In Section 4 below, we investigate this deviation from theory by hypothesizing noisy responses on the seller side.

We now turn to the question of convergence over rounds. Figure 2 displays the average posted prices and transaction prices per period by treatment. Treatments $T_2^n$ and $T_3^n$ evidently deviate substantially from the theoretical predictions, and do not seem to converge to it. For the other treatments prices seem to approach the equilibrium value, or some value close to equilibrium, fairly rapidly, and then remain there. In Appendix 6.3 we run dynamic regressions to check formally for convergence. These regressions show that, in a strict sense, we can only be confident that posted prices weakly converge to the equilibrium value for treatment $T_3^c$. In the other treatments there is evidence of weak convergence, and with the exception of treatments $T_2^n$ and $T_3^n$, these processes converge to a value close to the theoretical prediction.

We now take a closer look at the theoretical and empirical price distributions for treatments $T_1^n$, $T_2^n$ and $T_1^c$, where theory predicts that sellers randomize over prices according to the distributions given in Table 2. Figure 3 provides the relevant distributions. In the figure dashed lines indicate theoretical price distributions, while solid lines are empirical posted prices.

First, data match the support of the equilibrium distributions in these treatments reasonably well. Using all periods, about 68% of the data lie within the support in treatment $T_1^n$. The corresponding numbers for treatments $T_2^n$ and $T_1^c$ are 85% and 80%, respectively.[16]

For treatments $T_1^n$ and $T_1^c$ a similar reasoning applies. While data track the theoretical distributions reasonably well, the empirical distributions do not have the convex shape of the theoretical distributions.

[15] In addition, a two-sample Kolmogorov-Smirnov test for equality of distributions rejects the null that posted prices in treatments $T_2^c$ and $T_3^c$ are drawn from the same distribution ($p < 0.000$).

[16] This finding is robust over rounds. Using only periods 39 to 48 (where behavior should have stabilized) improves the number only slightly $T_1^n$ (to 72% of data lying within the support), while the numbers stay unchanged for the two other treatments. That a large share of the data lie within the support is perhapes not so surprising. A simple logic shows that prices below the lower bound of the support are dominated by the rip-off price of 100 ECU. As an example, consider $T_2^n$ where there are two informed buyers. If the seller succeeds in posting the lower price she sells two units to the informed buyers, and has an equal chance of selling her third unit to the uninformed buyer. Thus, *given* that the seller has the lower price the expected profit equals her posted price times 2.5. Posting the rip-off price of 100 provides an expectation of 50. Thus any price below $50/2.5 = 20$, which is the lower bound of the support, is dominated by the rip-off price.

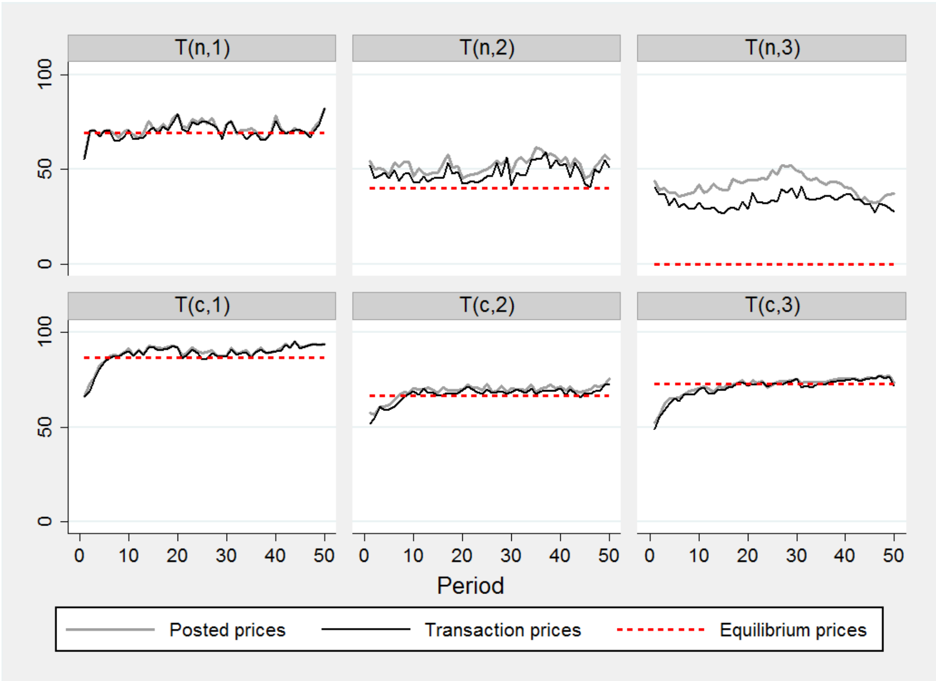


Figure 2: Average posted prices and average transaction prices over periods.

**Result 5 (Price distributions)** *In treatments $T_1^n$, $T_2^n$, and $T_1^c$, where theory predicts price distributions, the empirical distributions of posted prices roughly match their predicted counterparts. While the shape is not always well matched, the support is matched quite closely.*

Below we analyze how deviations from theoretical price distributions can be accounted for by noisy seller responses. Prior to that, however, we address the question of how consistent buyer responses are with theory.

**Buyer behavior** For the theoretical pricing strategies to make sense, sellers need to believe that buyers will respond optimally to the prices they post. Do buyers respond optimally to posted prices? In treatments $T_1^n$ to $T_3^n$ and $T_1^c$ the unconditional best response of an informed buyer is to (try to) purchase from the seller with the lower price. In these treatments a high fraction of purchase attempts follow the predicted best responses.

**Result 6 (Buyer behavior I)** *When prices between sellers differ, the average percentage of buyers that go for the lower price is 92.4 in treatment $T_1^n$, 98.6 in treatment $T_2^n$, 97.1 in treatment $T_3^n$, and 88.4 in treatment $T_1^c$.*[17]

In treatments $T_2^c$ and $T_3^c$ the equilibrium conditions require informed buyers to randomize over which seller to choose such as to make other informed buyers indifferent in their choice of a seller.

[17] The average payment in excess of the lower price paid by subjects in ECU (standard deviation) and by treatment was 13.5 (17.5) in $T_1^n$; 10.3 (16.7) in $T_2^n$ ; 11.1 (14.8) in $T_3^n$; 8.6 (10.1) in $T_1^c$; 6.2 (5.8) in $T_2^c$; and 8.2 (8.4) in $T_3^c$. In treatments $T_1^n$, $T_2^n$, $T_3^n$ and $T_1^c$ irrational buyer decisions are mainly due to one or two outlying subjects that make repeated - and often costly - mistakes. In $T_2^c$ and $T_3^c$ visiting the high price seller is more evenly distributed over buyers, as one would expect in equilibrium.

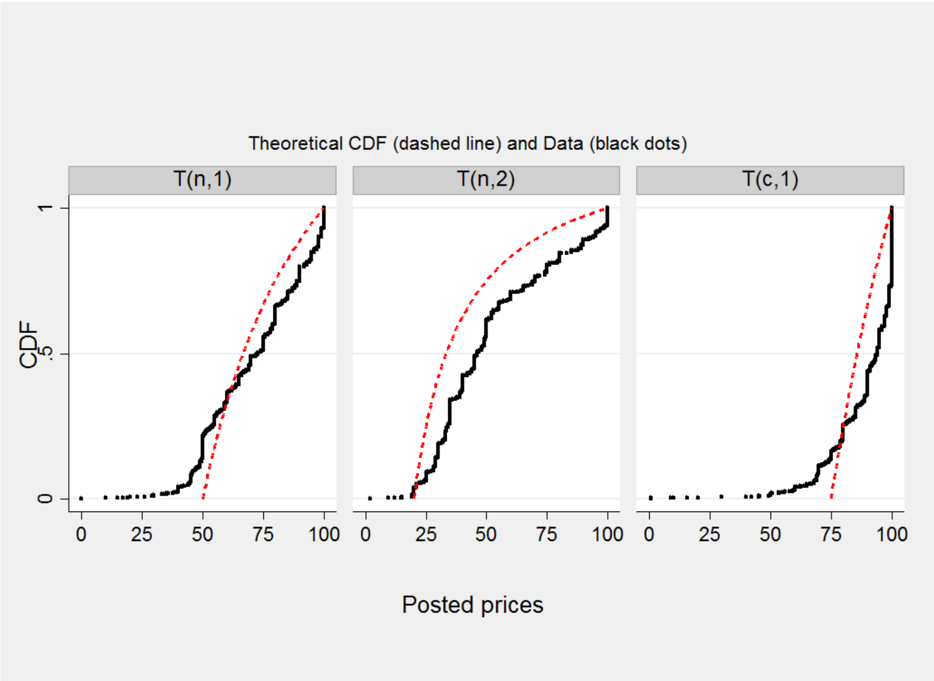


Figure 3: Cumulative price distributions $T_1^n$, $T_2^n$, and $T_1^c$: Data and theoretical prediction

To evaluate the optimality of buyer responses in these treatments we used the following procedure for each of these treatments. First we calculated for each informed buyer in every period the predicted equilibrium probability of choosing seller square, given the pair of actual prices posted. We then estimated a logistical regression. The dependent variable in this regression is a dummy equal to one if the buyer in question went to seller square, and zero otherwise. This dummy was regressed on the equilibrium probability of choosing seller square. The regressions were estimated with buyer random effects. Table 4 reports the results.

Table 4: Logistical regressions with random effects for buyers.

| Treatment | $T_2^c$ | $T_3^c$ |
|---|---|---|
| Equilibrium probability of choosing | 4.99*** | 3.69*** |
| seller "square" given posted prices | (.271) | (.263) |
| Constant | -2.53*** | -1.83*** |
| | (.192) | (.143) |
| # of data points | 1500 | 2250 |
| # of buyers | 30 | 45 |
| Log likelihood | -737.1 | -1436.5 |
| $\chi^2$ model | 338.8*** | 198.0*** |

*Dependent variable: choice of seller square. Standard errors in parentheses. Significant at level: *** 1 % ; ** 5 %; * 10 %.*

The regression coefficients are precisely estimated, the fit of the models is good in each case, and the probability of choosing seller square, given a pair of prices, is positively and significantly related to the theoretical probability of making such a choice in both treatments. Taking exponents on both sides of the regressions and reorganizing, we obtain the estimated probabilities of choosing seller square for each observation (each buyer in each period) in each treatment. Averaging over the theoretical and the estimated probabilities (of choosing square) for each treatment, returns the results reported in Table 5.

Table 5: Average equilibrium- and estimated probability of choosing square

| Treatment | $T_2^c$ | $T_3^c$ |
|---|---|---|
| Equilibrium probability | .542 | .508 |
| Estimated probability | .541 | .511 |

Figure 4 shows that these averages do not mask a weak buyer response to changes in the theoretical probability. In the figure circles provide the average fraction of buyers visiting seller square (y-axis) for brackets of length 0.025 on the theoretical probability of doing so (x-axis). If the theoretical probability is a perfect predictor of the actual choices, all circles will be located on the (dashed) 45-degree line.

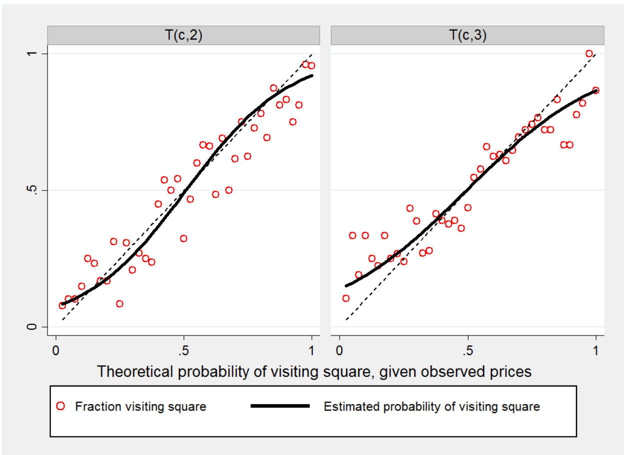


Figure 4: Estimated and actual buyer reactions in treatments $T_2^c$ and $T_3^c$

From Figure 4 we conclude that the theoretical probability has substantial predictive power over it's entire range. The black lines are estimated probability curves, using the regressions in Table 4. We appreciate that these curves are close to linear over the range of the theoretical probability, indicating the absence of threshold effects. The slope of the estimated probability curve is closer to unity for $T_2^c$ than for $T_3^c$, were buyers overshoot somewhat for low theoretical probabilities, and undershoot somewhat for high theoretical probabilities. Still, the general impression is that theoretical choice probabilities are remarkably close to the actual ones also in $T_3^c$.

**Result 7 (Buyer behavior II)** *For treatments $T_2^c$ and for $T_3^c$ the average probability of buying at a specific seller is almost identical to the average predicted probability given prices. The estimated probabilities follow the predicted probabilities very closely.*

Surprisingly, informed buyer responses seem, if anything, to correspond better with theory when responses are more complicated to work out (i.e. when mixed strategies are required) than when they are not (i.e. where buyers have dominant pure strategies).

Given that buyer responses are very close to the theoretical predictions for treatments $T_2^n$, $T_3^n$, $T_2^c$, and $T_3^c$, and fairly close for treatments $T_1^n$ and $T_1^c$, we need to investigate the sources of deviations coming from seller behavior given optimal buyer behavior.

**Seller behavior** In the following we analyze the seller behavior observed in the experiments. Particularly for the treatments with capacity constraints, average prices match prices predicted by theory surprisingly well. The predicted price distributions of treatments $T_1^c$, $T_2^n$, and, to a lesser extent, of treatment $T_1^n$ are also quite closely matched, although they have slightly different shapes than their theoretical counterparts. Deviations from expected prices are most pronounced in the Bertrand case ($T_3^n$) and in treatment $T_2^n$, both of which feature no capacity constraints.

We first analyze whether and to what extent these deviations can be rationalized by noisy, or probabilistic, best responses within a quantal response equilibrium (QRE). Subsequently, we explore a beliefs-based argument in which sellers attach a positive probability on opponents being "noise-players", and optimize against this belief.

With quantal responses all actions are taken with positive probabilities, but the probability of taking an action increases with it's expected profit. The equilibrium restriction of QRE is that each player holds correct beliefs about the probability distribution over the choices of the other players.[18] As argued above, buyers' behavior in the second stage is close to optimal in our experiments. In the following we therefore take optimal buyer choices conditional on posted prices as given and restrict our attention on noisy best responses of sellers.

Let $F_i^Q(p)$ indicate the probability that seller $i$ posts a price less than or equal to $p$, and let $E\pi_i(p', F_{-i}^Q)$ denote seller $i$'s expected profit of posting price $p'$ when the pricing strategy of the other seller is given by the cumulative distribution function $F_{-i}^Q$. Furthermore, let $T_i$ be a mapping of the expected profit of seller $i$ into $F_i^Q(p)$. QRE is defined as a pair of strategies $\left\{F_i^Q, F_{-i}^Q\right\}$ such that for any price $p' \in [0,1]$ and for each seller $i$ we have that $F_i^Q(p') = T_i(E\pi_i(p', F_{-i}^Q))$, where $E\pi_i(p, F_{-i}^Q)$ is the expected profit of player $i$ choosing $p$' given the price distribution of the other player. In the following we employ the logit specification of QRE, where the underlying error on expected profits follows an extreme value distribution. Assume $0 \leq \lambda$ and let the mapping from expected profits to choice probabilities have the following form:

$$T_i(E\pi_i(p, F_{-i}^Q)) \equiv \frac{1}{d}\int_0^p exp(\lambda E\pi_i(x, F_{-i}^Q))dx, \quad \text{with } d \equiv \int_0^{p_{max}} exp(\lambda E\pi_i(x, F_{-i}^Q))dx$$

When $\lambda$ approaches zero, all prices are equally likely, which can be interpreted as completely noisy strategies. On the other extreme, if $\lambda$ goes to infinity, the quantal response approaches the best response of the underlying pricing game, and behavior converges to a Nash-equilibrium.

QRE has been criticized for being too flexible in capturing observed choices.[19] We therefore estimate the QREs for all treatments simultaneously in addition to estimating a QRE for each treatment individually.

[18]QRE was first introduced by McKelvey and Palfrey (1995). The noise in the decision process can be rationalized by assuming unobserved heterogeneity in the utility functions of sellers (McFadden (1974)), or irrational trembles as in Luce (1959), and Luce (1977).

[19]See e.g. Haile, Hortaçsu, and Kosenok (2008).

The QRE distributions was solved using a numerical approximation to a grid with integer prices $0, 1, 2, ..., 100$. Distributions were then fitted to observed posted prices using a maximum likelihood approach. Table 6 reports the parameter estimates, the implied expected prices as well as the log-likelihoods.

Table 6: QRE estimates

| Treatment | $T_1^n$ | $T_2^n$ | $T_3^n$ | $T_1^c$ | $T_2^c$ | $T_3^c$ |
|---|---|---|---|---|---|---|
| $\lambda$ | 4.4 | 10.4 | 4.2 | 12.4 | 17.0 | 5.4 |
| Expected price | 70.5 | 49.7 | 39.9 | 83.9 | 70.4 | 54.6 |
| Log-Likelihood | -6394 | -6602 | -6594 | -5475 | -5819 | -6578 |
| $\lambda$ | 7.5 | | | | | |
| Log-likelihood | -38024 | | | | | |
| Expected price | 72.2 | 51.6 | 32.8 | 79.5 | 67.0 | 56.9 |

*Maximum likelihood estimation on a grid of integer prices. With simultaneous estimation each treatment receives the same weight in the likelihood function.*

Figure 5 shows the fitted distributions and the data.

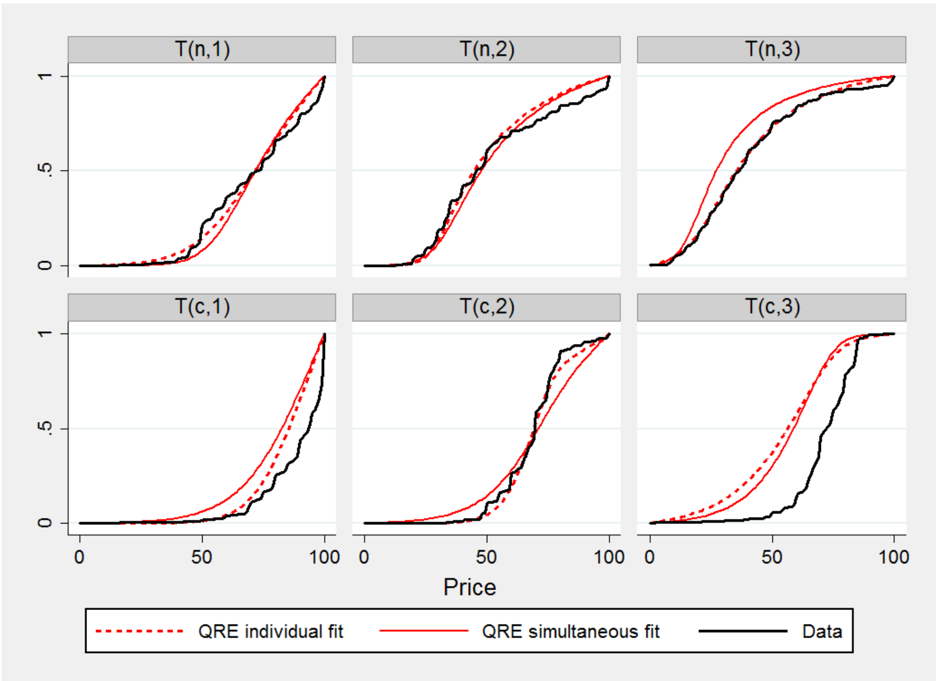


Figure 5: QRE distributions and actual posted price distributions.

While the QRE distributions only roughly approximate the actual ones,[20] several features are remarkable. First, compared to the distributions predicted by theory in treatments $T_1^n$, $T_2^n$, and $T_1^c$ shown in Figure 3, the shapes implied by the QRE distributions are much more in line with the

[20] The empirical average prices by about 11% on average from the ones implied by the QRE distributions using the simultaneous estimation (for the individually estimated QRE distributions this deviation becomes 8%). A substantial part of this is due to the mismatch in treatment $T_3^c$.

data. However, the average prices implied by the QRE distributions are not much closer to the data than the theoretical expected prices for those three treatments. Further, in the case of treatments $T_2^c$ and $T_3^c$, where theory predicts point prices, QRE can rationalize the observed price distributions. Regarding treatments $T_2^n$ and $T_3^n$ we find that noisy seller responses can help to understand the large deviations from the Nash equilibrium. Furthermore, for all treatments, except $T_3^c$ the average price of the data is reasonably matched by the individually fitted distributions.

**Result 8 (Seller behavior I)** *The individual QRE distributions roughly match the empirical distributions of $T_1^n$ to $T_2^c$. ORE distributions partly rationalize the observed price dispersion in treatments $T_2^c$ and for $T_3^c$. Furthermore, QRE account well for the substantial deviations from Nash equilibrium in treatments $T_2^n$ and $T_3^n$.*

To better understand why some of the treatments lead to stronger deviations from equilibrium than others we consider an argument in the spirit of Dufwenberg et al. (2000). We assume that sellers entertain the belief that any opponent she meets will deviate from the optimal strategy with positive probability by playing a behavioral mixed strategy. In the following we consider only the best response to such beliefs, but we are agnostic about possible equilibrium outcomes. Our examples suggest that the optimal price set by a capacity constrained seller is highly robust to the particular belief she holds about the noisy response of the opponent. Furthermore, with capacity constrained sellers the optimal price corresponds closely to the Nash price of the underlying market game. In contrast to this, the optimal price set by a seller without capacity constraints is much more sensitive to the belief she holds about the noise of the opponent. Furthermore, without capacity constraints the optimal price price deviates substantially from the Nash price. In particular the optimal price is far above the Nash price in $T_2^n$ and (particularly) in $T_3^n$.

To be concrete, let the expected profits of a seller be a function of her own price and a partly behavioral strategy of the other seller. By "partly behavioral" we mean that the price distribution the other seller uses is a convex combination of the equilibrium price distribution from theory and a behavioral price distribution. We consider three examples, a mixture of the equilibrium distribution with a price distribution that is positively skewed ($F(p_{-i}) = \sqrt{p_{-i}/100}$), one with a uniform distribution, and one with a negatively skewed distribution ($F(p_{-i}) = (p_{-i}/100)^2$). We set the weight of the behavioral distribution to 25%. The qualitative results remain the same if this weight is reduced. In treatments $T_1^n$, $T_2^n$, and $T_1^c$, where theory implies mixed strategy equilibria even small noise is likely to move the profit maximizing price as profits given by theory are constant along the support of equilibrium prices.

Looking at 6, it is striking how closely the maxima of expected profits match the Nash prices when sellers are capacity constrained (dashed vertical lines), but not when sellers can supply the whole market and buyers are informed. Furthermore, the distances of the maxima of the expected profits to the Nash prices are strongly correlated to the differences of the empirical average prices (solid vertical lines) to the Nash prices across treatments.

For all examples of mixed price distributions the maxima are at significantly higher prices than the predicted ones, in partiuclar in treatments $T_2^n$ and $T_3^n$. For the Bertrand treatment this is very intuitive as the Nash equilibrium strategy gives a payoff of zero and therefore is weakly dominated by any other strategy. Even when the weight of the noisy strategy is very small, the optimal price is far from zero. When some buyers become uninformed, the strategic considerations regarding the informed become less important. Instead, pricing choices become more dominated by the gain from selling to an uninformed buyer, which is independent of the opponent's strategy. Thus, the impact of the behavioral strategy decreases.

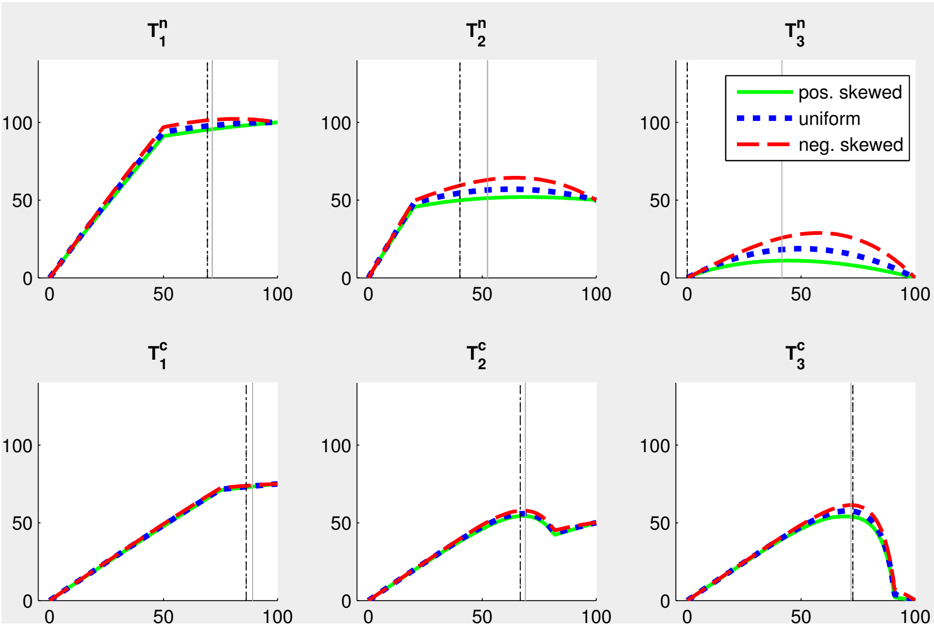


Figure 6: Expected profits as function of the own price given a 75-25 mixture between the equilibrium distribution and a "noisy" distribution of the other player. Vertical dashed lines indicate theoretical expected prices and solid lines average prices in the data.

For treatments $T_1^n$ and $T_1^c$ the maxima are somewhat to the right of the predicted expected prices, but the profit functions are also relatively flat at the maximum, giving only low incentives to deviate upwards. For treatment $T_3^c$ the maximum for the distributions that include mixtures with the uniform and the positively skewed distributions are to the left of the equilibrium price. We do not observe such a deviation in the data. It might help to explain, however, why the QRE estimates lead to much lower expected prices (see table 6).

**Result 9 (Seller behavior II)** *A seller's optimal price, given a belief that opponents may be noise players, corresponds to observed deviations from Nash equilibrium, both in direction and magnitude.*

**Comparison to previous experiments.** How do our results compare to existing ones? Cason and Noussair (2007) (hereafter CN) test the Burdett, Shi, and Wright (2001) model. Our design is very close to theirs. CN find average posted prices of 83.7 for periods 39-48.[21] In comparison, average posted prices in periods 39-48 is 75.2 in our $T_3^c$ treatment. So, while CN overshoot the equilibrium value by 11 percentage points in these 10 periods, we overshoot by only 2.2 percentage points. Finally, our data converge more rapidly on a value closer to equilibrium in the $T_3^c$ treatment than the CN data does.[22]

Anbarci and Feltovich (2014) (hereafter AF) also run a $T_3^c$ treatment. Their design differs from ours (and that of CN) in important ways.[23] They run their $T_3^c$ treatment for 20 periods. Averaging

[21] After behavior has stabilized, but before the end game effects set in.

[22] To see this, compare the dynamic regressions in the appendix of this paper with those in CN.

[23] AF run the same subjects in various treatments, using only three separate matching blocks. The design combine within -and between subjects comparisons, controlling for order effects.

posted prices over all periods, AF undershoot the equilibrium value by 13.5 percentage points.[24] Averaging posted prices only over the last 5 periods reduces this undershooting to 7.9 percentage points.

In general, buyer reactions in our $T_3^c$ treatment are substantially more in line with theory than those of CN and AF. While we observe the same *qualitative* biases in buyer reactions as AF and CN, these biases are far weaker in our $T_3^c$ treatment than in theirs.[25]

Morgan, Orzen, and Sefton (2006) (hereafter MOS) test the Varian (1980) model. Their design differs from ours in a number of ways.[26] In their two-seller treatments, they test for the change in posted prices as the fraction of informed buyers is increased from $\frac{1}{2}$ to $\frac{5}{6}$. Their qualitative results are in line the results we obtain for $T_2^n$ and $T_1^n$. Increasing the share of informed buyers reduces posted prices, as it should do in equilibrium. As in our $T_2^n$ and $T_1^n$ treatments, the overshooting of posted prices compared to equilibrium values increases substantially with the fraction of informed buyers.[27]

As in our $T_2^n$ and $T_1^n$ treatments, the support of the empirical price distributions match the support of the theoretical price distributions well in the two-seller treatments of MOS. Furthermore, and again as in our $T_2^n$ and $T_1^n$ treatments, empirical price distributions in MOS are somewhat closer to theoretical distributions the larger the fraction of informed buyers is.

Several tests of Bertrand (1884) doupoly competition exist. In Dufwenberg and Gneezy (2000) (hereafter DG), and in Dufwenberg, Gneezy, Goeree, and Nagel (2007) (hereafter DGGN) buyer reactions are automated, and treatments are conducted with pen and paper. In DG marginal costs are 1 and in DGGN 2, while buyer valuations are 100 in both experiments. Sellers compete for 10 periods. Average posted (transaction) prices over these 10 periods are 34.5 (27.1) in DG and 28.7 (21.9) in DGGN.

In Abrams, Sefton, and Yavas (2000) (hereafter ASY) sellers and buyers were randomly matched, and buyers had the opportunity to search at a cost after a match was formed and posted prices had been observed.[28] Buyers and sellers were humans, the exeperiment lasted for 25 periods, and was computerized. Buyer valuations were set at 120 and marginal costs at 0. Rescaled to a valuation of 100 the average posted prices over the 25 periods were 40.5, while the average transaction prices were 24.2. Common to DG, DGGN and ASY is that prices are volatile and do not drop monotonically over time towards the equilibrium in which prices equate marginal costs.

In our $T_3^n$ treatment average posted prices over all periods were 41.0, while average transaction prices were 33.2. The time paths of average posted and transaction prices are displayed in figure 2. As is evident, neither price measure falls monotonically over time. Thus, our $T_3^n$ results are comparable to those of DG, DGGN and ASY in the sense that prices deviate substantially from equilibrium and stay in the same broad range as in existing experiments; that transaction prices are substantially below posted prices; and that prices do not fall monotonically over time.

[24]Average transaction prices over all rounds undershoots the equilibrium value of the $T_3^c$ treatment by a full 14.4 percentage points in AF. In an identical design by Anbarci and Feltovich (2013), undershooting in the $T_3^c$ treatment is reduced to 7.1 percentage points (compare table 2 in AF with table 5 in Anbarci and Feltovich (2013)).

[25]Compare our figure 4 with figure 4 in CN and figure 4 in AF.

[26]Among other things they ran the same subjects in various treatments, using six separate matching blocks, combining a within -and between subjects design with control for order effects. In contrast to our design, MOS also used robots to mimic the responses of informed as well as uninformed buyers.

[27]In the MOS treatment with 1/2 of buyers informed overshooting is 5.3 percentage points, while it increases to 15.4 percentage points in the treatment with 5/6 of buyers informed. In our $T_1^n$ treatment (1/3 of buyers informed) the overshooting is 1.8 percentage points, compared to 11.9 percentage points in our $T_2^n$ treatment (2/3 of buyers informed).

[28]The search opportunity should be of no consequence in the Bertrand treatments, and is generally not used.

Summing up, we succeed in replicating the behavioral patterns of existing experiments for treatments $T_1^n$, $T_2^n$, $T_3^n$, and $T_3^c$. This increases the credibility of our test of Lester's paradox.

## 5 Conclusion

In this paper we have tested the effects of information and coordination frictions due to capacity constraints in small posted offer markets. Our experiments have confirmed the theoretical predictions that the presence of capacity constraints dramatically changes the effect of an increased share of informed buyers. In the absence of of capacity constraints prices clearly fall as more buyers become informed. In the presence of capacity constraints prices fall only slightly, or even increase as more buyers become informed. Our experiment confirms the counterintuitive prediction of Lester's paradox. In addition, our experiments demonstrate that different market settings lead to differently strong deviations from theory. Our results indicate that these deviations are mostly due to deviating seller behavior and not so much due to buyers' choices. Noisy price setting, or beliefs about noise in the price setting, can rationalize the observed price choices.

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# 6 Appendix

## 6.1 Some Calculations for the Theoretical Predictions

Here are the predictions for the cases of $S = 2$ and $B = 3$, with $N > 0$. For the case without capacity constraints with $N < 3$ we can easily integrate (2) to get:

$$E[p] = -\frac{3-N}{2N} \ln \frac{3-N}{3+N}.$$

Similarly, for the expected minimum price we obtain:

$$E[p_{\min}] = \frac{3-N}{N} + \frac{(3-N)^2}{2N^2} \ln \frac{3-N}{3+N.}$$

Plugging in the values $N = 1$ and $N = 2$ gives the results in table 2.

For the capacity constraint case with $N = 1$ we have

$$E[p] = \frac{p_0}{1-p_0} \ln p_0 = -3\ln(3/4) \approx 0.863$$

The expected minimum price is

$$E[p_{min}] = p_0 + (\frac{p_0}{1-p_0})^2(p_0^{-1} + 2\ln p_0 - p_0) \approx 0.822,$$

where $p_0 = 3/4$.

Expected transaction prices in treatments $T_1^n$, $T_2^n$, and $T_1^c$ can be computed by using the above given average and minimum prices or directly by dividing total profits in the market (which equal the sum of prices) by the expected number of transactions.

**Treatment $T_1^n$:** As all choices give the same profits in equilibrium, expected profits of a seller equals the rip-off price of one times the expected number of goods sold to the uninformed buyers. Total profits in the market with two sellers are therefore $2 \cdot (\frac{1}{4} \cdot 1 + \frac{1}{4} \cdot 1 + \frac{1}{4} \cdot 2 + \frac{1}{4} \cdot 0) \cdot 1 = 2$. The expected number of sales is 3 as all buyers will obtain a good. Thus average profit and price equals $E[p_T] = 2/3 \approx .667$.

**Treatment $T_2^n$:** The same reasoning as before applies. Total profits divided by the expected number of transactions gives: $E[p_T] = \frac{2 \cdot (\frac{1}{2} \cdot 1 + \frac{1}{2} \cdot 0) \cdot 1}{3} = 1/3 \approx .333$.

**Treatment $T_1^c$:** The probability of meeting the uninformed is given by $1 - (1 - 1/S)^U = 3/4$ in this case. The expected number of total transactions is 1 for the seller with the lower price as that seller always gets at least the informed buyer. The other buyer gets an uninformed with probability 3/4. Total profits per transaction are then $E[p_T] = \frac{2 \cdot 3/4 \cdot 1}{7/4} = 6/7 \approx .857$.

## 6.2 Buyer responses z=c case

Here we compute the individual buyer's best response functions $\theta^1(p_1, p_2)$ from the indifference condition $\eta^c(\theta^1)(1 - p_1) = \eta^c(1 - \theta^1)(1 - p_2)$ for cases $N = 2$ and $N = 3$.

$N = 2$ case:

$$\theta^1(p_1, p_2) = \begin{cases} 0.5 & \text{if } p_1 = p_2 \\ 0 & \text{if } 4 + 5p_2 - 9p_1 < 0 \\ 1 & \text{if } 4 + 5p_1 - 9p_2 < 0 \\ \frac{4+5p_2-9p_1}{4(2-p_1-p_2)} & \text{o.w.} \end{cases}$$

$N = 3$ case:

$$\theta^1(p_1, p_2) = \begin{cases} 0.5 & \text{if } p_1 = p_2 \\ 0 & \text{if } 2 + p_2 - 3p_1 \leq 0 \\ 1 & \text{if } 2 + p_1 - 3p_2 \leq 0 \\ \frac{(4-3p_1-p_2-\sqrt{16(1-p_1-p_2)+22p_1p_2-3(p_1^2+p_2^2)}}{2(p_2-p_1)} & \text{o.w.} \end{cases}$$

## 6.3 Dynamic regressions

We address the question of convergence running dynamic regressions treatment by treatment (Noussair, Plott, and Riezman (1995), Noussair, Plott, and Riezman (1997), and Cason and Noussair (2007)) . Two specifications are employed. In the first specification $y_{it} = \sum_{i=1}^{5} \beta_{1i} D_i(1/t) + \sum_{i=1}^{5} \beta_{2i} D_i((t-1)/t) + \mu_{it}$, were $i$ indicates block and $t \in [1, \bar{t}]$ indicates period. The $(t - 1/t)$ terms take the value 0 in period 1, thus $\beta_{1i}$ provides an estimate of the value of $y_{i1}$ for block $i$. As $t$ grows the $(t-1)/t$ terms approach 1 and the $1/t$ terms approach 0, thus $\beta_{2i}$ is an estimate of the asymptote of $y_{iT}$. The criteria for convergence are as follows. The process is said to exhibit strong convergence if $H_0^A$: $\beta_{21} = \beta_{22} = ... = \beta_{25}$ cannot be rejected. The process is said to exhibit weak convergence if $\beta_{i2}$ is closer to the equilibrium value of the treatment than is $\beta_{i1}$.

In the second specification $y_{it} = \sum_{i=1}^{5} \beta_{1i} D_i(1/t) + \beta_2((t-1)/t) + \mu_{it}$, $\beta_2$ provides an estimate of the extent to which the process converges on the equilibrium. The process is said to converge on the equilibrium if $H_0^B$: $\beta_2 = \textit{equilibrium value}$ cannot be rejected.

We estimate the regressions with random intercepts for subjects, and corrected standard errors for correlation over panels (Prais-Winsten regression). In both specifications we follow the experimental literature and exclude the last two periods from the estimations, so that $\bar{t} = 48$.[29] Table 7 provides the estimates for posted prices with the first specification, table 8 provides the estimates for posted prices with the second specification.

Table 7: Convergence regressions

| Tr | $\beta_{11}$ | $\beta_{12}$ | $\beta_{13}$ | $\beta_{14}$ | $\beta_{15}$ | $\beta_{21}$ | $\beta_{22}$ | $\beta_{23}$ | $\beta_{24}$ | $\beta_{25}$ | $H_0^A$ | $E(p)$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $T_1^n$ | 50.6 | 66.9 | 46.4 | 62.9 | 57.7 | 77.5 | 63.1 | 68.8 | 87.1 | 66.4 | .000 | 69.2 |
| | (5.77) | (7.50) | (8.92) | (4.69) | (7.73) | (1.42) | (1.85) | (2.19) | (1.16) | (1.90) | | |
| $T_2^n$ | 56.9 | 54.4 | 51.3 | 57.5 | 50.2 | 51.0 | 50.5 | 51.7 | 59.9 | 46.6 | .000 | 40.2 |
| | (9.28) | (7.96) | (8.43) | (9.58) | (5.48) | (2.56) | (2.19) | (2.32) | (2.64) | (1.51) | | |
| $T_3^n$ | 49.0 | 37.4 | 60.2 | 35.6 | 50.9 | 51.1 | 25.3 | 36.9 | 51.6 | 37.4 | .000 | 0.0 |
| | (8.08) | (7.44) | (6.25) | (9.34) | (8.37) | (2.50) | (3.30) | (1.94) | (2.89 | (2.59) | | |
| $T_1^c$ | 58.6 | 57.8 | 78.3 | 55.9 | 80.1 | 98.5 | 93.5 | 90.6 | 86.2 | 87.5 | .000 | 86.3 |
| | (2.91) | (5.39) | (4.86) | (4.32) | (3.00) | (0.80) | (1.49) | (1.33) | (1.19) | (0.83) | | |
| $T_2^c$ | 62.9 | 57.5 | 53.0 | 52.6 | 61.2 | 67.6 | 73.5 | 68.2 | 76.2 | 64.0 | .000 | 66.7 |
| | (3.85) | (2.93) | (6.37) | (3.54) | (2.66) | (1.11) | (0.85) | (1.84) | (1.03) | (0.77) | | |
| $T_3^c$ | 47.6 | 49.3 | 57.3 | 55.3 | 57.3 | 67.6 | 80.0 | 76.1 | 69.6 | 75.1 | .000 | 72.7 |
| | (5.14) | (3.85) | (1.92) | (2.52) | (3.38) | (1.65) | (1.24) | (0.62) | (0.81) | (1.09) | | |

*Dependent: posted prices. Prais-Winsten regressions treatment by treatment, with seller random effects. Coefficients (standard errors).*

From Table 7 we observe that for treatments $T_1^c$ to $T_3^c$ each $\beta_{i2}$ term is closer to the equilibrium price than its corresponding $\beta_{i1}$ term. In treatments $T_1^n$ to $T_3^n$ a slim majority - three of five - $\beta_{i2}$ terms are closer to equilibrium than their corresponding $\beta_{i1}$ terms. Thus, for treatments $T_1^c$ to $T_3^c$ there is clear evidence of weak convergence towards equilibrium, while the evidence is not as strong for treatments $T_1^n$ to $T_3^n$. In all treatments the null that all $\beta_{i2}$ terms are equal can be rejected with high degree of certainty. Thus, convergence is not strong in any treatment.

Next, consider Table 8. Except for treatments $T_2^n$ to $T_3^n$, the estimate of $\beta_2$ is less than five points from the equilibrium value. In treatment $T_2^n$ and especially in treatment $T_3^n$, the deviations are substantial. Except for treatment $T_3^c$, the null of no difference between $\beta_2$ and the equilibrium can be rejected. In treatment $T_3^c$ this null cannot be rejected.

The variance of posted prices generally declines over time in each treatment. Except for $T_2^n$ variance declines in a majority of the matching blocks, and in $T_1^n$, $T_1^c$ and $T_3^c$ variance declines inn all five matching blocks, as shown in table 9. Qualitatively, the regressions are consistent with posted prices converging to a common value in these treatments. However, the null that $\beta_{21} = \beta_{22} = ... = \beta_{25}$ cannot be rejected with any degree of confidence.

[29]The reason for this is to remove end game effects that are likely to be present in experiments were subject the final period is public knowledge (see Cason and Noussair (2007), note 7 with references).

Table 8: Equilibrium convergence

| Tr | $\beta_{11}$ | $\beta_{12}$ | $\beta_{13}$ | $\beta_{14}$ | $\beta_{15}$ | $\beta_2$ | $E(p)$ | $H_0^B$ |
|---|---|---|---|---|---|---|---|---|
| $T_1^n$ | 56.2 | 57.6 | 42.4 | 73.8 | 50.6 | 72.7 | 69.2 | .000 |
| | (6.55) | (9.50) | (9.62) | (8.97) | (8.79) | (0.91) | | |
| $T_2^n$ | 56.2 | 53.3 | 51.1 | 63.1 | 46.2 | 52.0 | 40.2 | .000 |
| | (9.04) | (7.82) | (8.22) | (10.28) | (6.03) | (1.00) | | |
| $T_3^n$ | 52.7 | 34.1 | 59.1 | 41.9 | 48.3 | 40.0 | 0.0 | .000 |
| | (9.43) | (9.87) | (6.61) | (10.03) | (8.44) | (1.08) | | |
| $T_1^c$ | 63.7 | 59.5 | 78.4 | 53.1 | 77.9 | 91.2 | 86.3 | .000 |
| | (4.66) | (5.58) | (4.94) | (5.05) | (3.55) | (0.69) | | |
| $T_2^c$ | 61.7 | 59.8 | 54.3 | 56.2 | 59.5 | 69.8 | 66.7 | .000 |
| | (4.10) | (3.43) | (6.63) | (4.71) | (3.88) | (0.70) | | |
| $T_3^c$ | 47.1 | 51.3 | 57.7 | 54.7 | 58.7 | 73.6 | 72.7 | .173 |
| | (5.85) | (4.78) | (2.25) | (3.11) | (3.45) | (0.67) | | |

*Dependent: posted prices. Prais-Winsten regressions treatment by treatment, with seller random effects. Coefficients (standard errors).*

Table 9: Variance in posted prices

| | $\beta_{11}$ | $\beta_{12}$ | $\beta_{13}$ | $\beta_{14}$ | $\beta_{15}$ | $\beta_{21}$ | $\beta_{22}$ | $\beta_{23}$ | $\beta_{24}$ | $\beta_{25}$ | $H_0^A$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $T_1^n$ | 1280.5 | 427.7 | 746.6 | 1493.8 | 1076.5 | 120.3 | 324.6 | 408.0 | 53.1 | 269.2 | .000 |
| | (98.0) | (135.6) | (177.1) | (102.0) | (177.7) | (21.0) | (29.1) | (38.0) | (21.9) | (38.1) | |
| $T_2^n$ | 484.4 | 293.5 | 143.6 | 89.9 | 1168.7 | 451.7 | 623.3 | 555.5 | 576.3 | 666.5 | .035 |
| | (220.9) | (255.5) | (258.7) | (236.1) | (208.8) | (49.0) | (56.7) | (57.4) | (52.4) | (46.3) | |
| $T_3^n$ | 144.3 | 446.4 | 821.6 | 605.2 | 396.4 | 460.5 | 279.9 | 147.5 | 257.2 | 454.5 | .061 |
| | (309.7) | (322.6) | (160.0) | (195.0) | (357.0) | (101.2) | (105.4) | (52.3) | (63.7) | (116.7) | |
| $T_1^c$ | 346.3 | 1306.7 | 502.7 | 1058.6 | 258.8 | 14.5 | 48.4 | 144.2 | 66.1 | 141.1 | .000 |
| | (49.5) | (207.2) | (171.7) | (114.7) | (50.2) | (11.0) | (45.9) | (38.0) | (25.4) | (11.1) | |
| $T_2^c$ | 648.6 | 412.0 | 453.9 | 51.8 | 72.5 | 139.7 | 21.7 | 148.9 | 60.4 | 124.6 | .000 |
| | (88.3) | (36.0) | (97.6) | (52.8) | (81.6) | (18.8) | (7.7) | (20.8) | (11.2) | (17.4) | |
| $T_3^c$ | 890.6 | 900.4 | 192.7 | 62.5 | 811.3 | 50.4 | 60.2 | 66.4 | 25.4 | 77.2 | .003 |
| | (132.6) | (143.2) | (45.6) | (37.8) | (41.8) | (33.1) | (35.7) | (11.4) | (9.4) | (10.4) | |

*Dependent: Variance in posted prices. Prais-Winsten regressions treatment by treatment, with seller random effects. Coefficients (standard errors).*