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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 affected by information frictions and capacity constraints. Information about prices or salaries is not always available before visiting a firm, or may be too costly to acquire. Furthermore, in some markets sellers can serve all customers, whereas in other markets sellers are constrained in their capacity. In labor markets, firms may or may not advertise wages, and may to a varying degree be capacity constrained depending on the number of equivalent open job slots they possess. In some retail markets, like the gasoline market, sellers are not capacity constrained, while buyers often have to visit the station to observe the price. In the customer-to-customer markets for used cars, by contrast, prices are advertised (although bargaining may occur), while the seller only has one car to sell and thus is capacity constrained.

The theoretical literature shows that even small changes in the capacity of sellers or the informedness of buyers can have a profound impact on market outcomes. Particularly, prices decrease sharply in the share of informed customers when capacity is not constrained, but might change little in the presence of such constraints. While the interactions between seller capacity and consumer information is well understood in theory, well-controlled empirical studies of such interactions are absent in the literature. This paper aims at filling the gap by setting up a laboratory experiment.

The results of our experiment confirm the different effects of higher informedness with and without capacity constraints. In particular, when sellers are capacity constrained prices fall little and may even increase as the number of informed buyers increase. However, our findings also indicate that as information increases, prices do not decrease as much as theory predicts when sellers do not face capacity constraints. This may imply that measures of consumer protection aiming at informing customers may be less effective in terms of reducing prices than previously thought. Our findings may also contribute to a more nuanced view regarding the potential consumer benefits of the rapid growth in essentially cost-free access to posted prices on the internet.

Our experiment is based on two strands of the theoretical literature on posted offer markets. One strand explores the effects of information frictions when sellers have unlimited capacity. Hence sellers can serve all buyers that show up, but some buyers are uninformed about prices. Varian (1980), Burdett and Judd (1983), Stahl (1989), and Janssen and Moraga-González (2004) analyze markets where only 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

Another strand of this literature, starting with Montgomery (1991) and developed further by, among others, Burdett, Shi, and Wright (2001), explores the effects of search frictions when sellers have limited capacity to serve customers. Buyers have perfect information about prices, demand one unit of the good, and decide independently which seller to approach. Sellers only have a limited number of goods for sale, which can be normalized to one. Some sellers may get many and some sellers no customers, and when a queue forms, only one buyer will be served. Consequently, a coordination friction arises, as some 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. When sellers are capacity constrained, buyers trade off the price with the probability of obtaining the good, the price elasticity of demand is lower and the market price is strictly above the price when sellers are not capacity constrained (the Bertrand price). If the buyer-seller ratio is high, sellers' may even set prices close to the buyers' willingness to pay.

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

In a recent paper, Lester (2011) combines these two strands of the literature, by introducing 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. Generally, prices respond less when the fraction of informed customers increase compared with the unconstrained case, and they may even increase. This counter-intuitive 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 construct a unified model framework that allows us to study the interaction between limited information and capacity constraints in the lab. To this end we run six treatments, with a varying number of informed buyers and of units for sale. In each treatment there are three buyers with a unit demand, and the number of informed buyers ranges from 1 to 3. There are two sellers who in the "unconstrained" treatments can serve the entire market, and in the "constrained" treatments can serve at most one customer. Sellers simultaneously advertise a price, and buyers subsequently and simultaneously decide which seller to approach.

Our main contributions are the following. First, our experimental results show that when firms are capacity constrained, prices react substantially less to an increase in the share of informed buyers than they do in the unconstrained case. This is true for any fraction of informed buyers. Furthermore, when the number of informed buyers goes from two to three (all buyers) in the unconstrained case, Lester's paradox emerges. The average price goes up and the increase in transaction prices is significant at 10% confidence level. This indicates that the postulated relationship between prices and buyer information is not a mere theoretical curiosity. Second, we find that the model generally predicts prices better when sellers are capacity constrained than when they are not. Specifically, in the treatments with 2 and 3 informed buyers deviations are strong. Using the concept of Quantal Response equilibrium we analyze how noisy pricing behavior impacts on market prices. This allows us to explain the observed differences in deviations from Nash-equilibria well. We find that a little noise can push prices substantially above the Nash equilibrium when sellers are unconstrained in capacity while deviations are very small when they are constrained. Third, our experiment includes several important posted-offer market arrangements as special cases and thus makes them comparable. In particular, our evidence on the varying impact of noise on best responses shows the value of such cross-market comparisons. Further, some of the market structures contained in our experiment have been tested in isolation before. As we replicate their main findings our results appear to be robust to variations in the experimental setup. We discuss these related experiments in detail in the last part of Section 4.

The paper is organized as follows. In the next section we outline and explain the predictions from theory using a unified environment for all six market structures. In section 3 we present our design and hypotheses. Section 4 presents our main results, analyzes buyer and seller behavior, and relates our findings to existing experiments. Section 5 concludes. All additional material is gathered in an online appendix.

2 Theoretical Predictions

In the following we briefly outline the theoretical framework on which our treatments are based and refer the reader to the supplementary online appendix 6.1 for the details. The framework encompasses the model of Lester (2011), the standard directed search model of Burdett, Shi, and Wright (2001), a version of Varian (1980),² and the classic Bertrand model as special cases.

 $^{^{2}}$ In contrast to Varian (1980), we set costs equal to a constant normalized to zero.

The economy is populated by a number of S = 2 sellers (or "firms") and B = 3 buyers, all of which are risk neutral.³ Buyers have a unit demand with a reservation price normalized to 100. The model consists of two stages: First, sellers simultaneously set and commit to prices $p_s \in [0, 100]$. In the second stage buyers simultaneously make buying decisions. A number $U \ge 0$ of uninformed buyers independently and randomly choose a seller, where each seller is visited with equal probability by a given buyer. Further, there are $N \ge 1$ (with N + U = 3) informed buyers who can costlessly observe all prices offered in the market and choose at which seller to buy.

Regarding the number of units each firm has for sale we distinguish between two cases. In the first case (denoted by index z = c), 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 (denoted by z = n) firms are not capacity constrained, and each firm has B units for sale. In this case a seller can always serve all the customers that show up. We then denote a specific market setting by T_N^z , summarizing the parameter constellation of $z \in \{c, n\}$ and $N \in \{1, 2, 3\}$ which we will vary in the experiment

For a given combination of z and N the expected payoff of a seller s is $\pi_s(p_s, p_{-s}) = \mu(p_s, p_{-s})p_s$, where $\mu(p_s, p_{-s})$ is the expected number of sales given the own price and the prices of other sellers. The expected payoff of a buyer *i* conditional on choosing a seller s is $v_i(\theta_{-i}^s) = \eta(\theta_{-i}^s)(1-p_s)$, where $\eta(\theta_{-i}^s)$ is the probability of getting the good at seller s given that the other buyers goes to the same seller with probability θ_{-i}^s in a symmetric equilibrium. If sellers are not capacity constrained, z = n, this probability is always equal to 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.⁴

When varying the number of informed buyers N and the capacity z, different kinds of equilibria emerge which we summarize in Table 1. With no capacity constraints and all three buyers informed, Bertrand competition emerges, and the equilibrium price is zero (T_3^n) . With uninformed buyers, the equilibrium price cannot be zero, as a seller can obtain a strictly positive profit by setting the price to 100 and rip off the uninformed buyers that come along. With two uninformed buyers (T_2^n) , a seller that sets a price of 100 obtains an expected profit of 100 (two uninformed buyers arrive with probability $\frac{1}{2}$ each). A seller that sets a price of 50 obtains the same expected profit if he attracts the informed seller with probability 1. It can be shown that in the resulting equilibrium, sellers randomize their prices on the interval [50, 100]. With only one informed buyer (T_1^n) sellers randomize on the interval [20, 100]. When comparing the treatments with no capacity constraints along the dimension of buyer informedness, the classic result that expected prices decline with Nemerges, since competition for informed buyers becomes more intense.

Second, when there are capacity constraints and only one informed buyer (T_1^c) , the informed buyer will always approach the seller with the lowest price. A seller that sets a price of 100 sells with probability $\frac{3}{4}$, and hence gets an expected profit of 75. If a seller sets a price of 75, and attracts the informed buyer with certainty, he also gets an expected profit of 75. It can be shown that in equilibrium, sellers randomize over the price interval [75, 100]. If there are capacity constraints and more than one informed buyer $(T_2^c \text{ and } T_3^c)$ buyers play (symmetric) mixed strategies so that in equilibrium they are indifferent between sellers. While in general there can be equilibria with

³The constraints on the number of agents are only imposed to focus on the more interesting cases.

⁴See also our discussion of collusion in section 4.

mixed strategies on the sellers' side, for the parameter constellations of our treatments there will be only symmetric equilibria where sellers play pure strategies.

Comparing to the equilibria without capacity constraints, we see that expected prices are higher for a given number of informed buyers, N (see Table 1). In stark contrast to the case of no capacity constraints the equilibrium price can increase in the number of informed buyers given S and B(Lester's paradox). In our setup this occurs when moving from T_2^c to T_3^c .

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 the 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. 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.

Table 1: Theoretical predictions: Expectation, support and distribution of prices

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

p: posted prices; p_T : transaction prices

3 Parameters and Procedures

To test the different predictions of an increase in informed buyers when there are capacity constraints compared to the case without such constraints we use a 2×3 design. The experiment consists of six treatments where we vary both the capacity constraint, i.e. z = c or z = n and the number (equivalently, the share) of informed buyers, i.e. N = 1, N = 2, and N = 3. Our design allows us to better isolate the effect of capacity constraints when varying buyer informedness. To have such an explicit comparison is particularly important as the theoretically predicted price increase from T_2^c to T_3^c is relatively small so that we initially did not expect to actually observe a price increase.

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. Each of our sessions consisted of either two or three blocks. Each session investigated only one treatment. 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 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.⁵

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 2 provides an overview of the experiment.

Table 2: T	reatments and blocks
	# of 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
$\overline{T_2^c}$	2	3
$\bar{T_3^c}$	2	3

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.⁶ 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

⁵Concerns that heterogeneous 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_2^c and 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. We discuss the issue of collusion in detail in the online appendix.

⁶A full set of instructions and sample screen can be found in the online appendix.

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.

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 (see Table 3 for the actual numbers).



Figure 1: Average posted prices and transaction prices for each treatment - Data and Theory.

Treatment	T_1^n	T_2^n	T_3^n	T_1^c	T_2^c	T_3^c
Posted Prices	71.4	52.3	41.6	89.1	68.9	71.9
Transaction Prices	68.8	44.3	32.2	88.0	66.5	70.3
Coefficient of Variation (Posted Prices)	0.27	0.45	0.55	0.15	0.17	0.17

Table 3: Observed average posted and average transaction prices

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 $T_3^{n.7}$ For both posted and transacted prices the predicted patterns are clearly visible: for a given number of informed buyers 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 theoretically 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. 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 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).⁸

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 the increase in transaction prices is weakly significant when going from T_2^c to T_3^c .

⁷In 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.

⁸With 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).

In appendix 6.2 we run treatment regressions. These regressions confirm the results from the non-parametric tests, but also indicate that results are neither driven by differences in lab population (Oslo versus Konstanz), the interaction of treatments and time, or idiosyncratic differences across blocks. We comment further on the coefficients of variation after looking at 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.⁹



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

We now take a closer look at the distribution of prices. In the last row of Table 3 we report the coefficient of variation of posted prices for each treatment. These correspond reasonably well to the theoretical coefficients of variation in the treatments where prices are dispersed in equilibrium. For treatment T_1^n the predicted (observed) coefficient of variation is 0.20 (0.27), for T_2^n the predicted (observed) coefficient of variation is 0.20 (0.27), for T_2^n the predicted (observed) coefficient is 0.48 (0.45), while in treatment T_1^c the predicted coefficient of variation is 0.08, about half of the observed one (0.15). Unlike predicted by theory, there is also dispersion in prices for the remaining three treatments. Prices are to a limited degree dispersed in treatments T_2^c and T_3^c , whereas there is large variation in prices in the Bertrand treatment. We explore these deviations from theory further below. In Figure 3 we compare the empirical distributions of treatments T_1^n , T_2^n and T_1^c to their theoretical counterparts.¹⁰ 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.¹¹ While data

⁹In Appendix 6.2 we run dynamic regressions to check formally for convergence. These regressions show that 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. The precise definitions of strong and weak convergence are provided in the appendix.

¹⁰See Table 1 for the distribution functions.

¹¹This finding is robust over rounds. Using only periods 39 to 48 (where behavior should have stabilized) improves



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

track the theoretical distributions reasonably well, the empirical distributions do not have the convex shape of the theoretical distributions.

Result 4 [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.¹²

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 5 [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 .¹³

¹³The 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

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 perhaps 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.

 $^{^{12}}$ Separate analysis of buyer and seller behavior is common in experiments where buyer reactions are not automated, see for instance Anbarci and Feltovich (2014) and Cason and Noussair (2007).

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. 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 a fixed seller, given the pair of actual prices posted. Recall that sellers have fixed labels in our experiment; either square or circle. In our calculations the fixed seller is the one labeled square. We then estimate a logistic 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. Table4 reports the results.

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
$\chi^2 \text{ model}$	338.8^{***}	198.0***

Table 4: Logistic regressions with random effects for buyers.

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

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.

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 its 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 , where 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 6 [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.

While we cannot easily compare them, it seems that informed buyer responses 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). In appendix 6.4 we investigate the confidence interval around the standard errors for the mean reactions of buyers in treatments T_2^c and T_3^c . In the vast majority of cases we are unable to reject the null of perfect match between theoretical and empirical choice probabilities using a 95 % confidence interval.

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 investigate the sources of deviations coming from seller behavior given optimal buyer behavior.

Seller behavior As buyers' decisions are by and large consistent with theory, the observed deviations from theory should primarily be caused by sellers' behavior. Figure 1 is suggestive about the pattern of deviations. First, the capacity constrained treatments are on average much closer to the theoretical predictions than the non-constrained treatments. Furthermore, in the absence of

capacity constraints the deviations become stronger as the share of informed buyers increases. The first observation may appear surprising as the capacity constrained treatments involve a seemingly more complex reasoning for both sellers and buyers.

We think that it is reasonable to assume that subjects in a laboratory setting make mistakes relative to the behavioral requirements of the equilibria. Errors seem to be more likely if they are associated with a smaller loss in profits. Furthermore, the effects of mistakes may depend on how the opponent firm reacts to them, i.e. the derivative of the best response function to a change in the opponent's price. To illustrate this we compare the (pure strategy) best-response functions across treatments. In the treatments without capacity constraints, $T_1^n - T_3^n$, as well as in treatment T_1^c , the best response to a price in the equilibrium support is to slightly undercut by setting the price ε below the competitor's price.¹⁴ Hence the best response to a deviation by the other seller in these treatments is to increase the price with the same amount. The reaction is much more muted in treatments T_2^c and T_3^c , where a unit price increase is only followed by a raise of 0.61 units.

The first row of Table 6 shows the best response to a unit increase of the opponent's price, starting from the equilibrium expected transaction price (where we approximate $\varepsilon \approx 0$). In all treatments prices move in the same direction, but the reactions are much weaker in the last two treatments. The two last rows of the table show the corresponding absolute and relative increases in profits, respectively. The changes in profits are stronger on average for the treatments without capacity constraints. Moreover, for these treatments the profit changes are more pronounced the more informed buyers there are. Thus, upward deviations are more likely to be reinforced in treatments T_2^n and T_3^n where profit changes are large.

Table 6:	Deviations	from	equilibrium
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Treatment	T_1^n	T_2^n	T_3^n	T_1^c	T_2^c	T_3^c
Best response price increase	1.00	1.00	1.00	1.00	0.61	0.61
Change in profits	2.00	2.50	3.00	1.00	0.88	0.88
% change in profits	1.50	3.00	∞	1.17	1.51	1.39

All measures are relative to the (expected) equilibrium transaction price reported in Table 1. "Best response price increase" refers to an optimal price increase when the opponent increases the price by one unit. The amount of undercutting is set to $\varepsilon = 0$. Both initial and resulting profits are calculated assuming that the player (marginally) undercuts the price.

In the Bertrand case, the Nash equilibrium price is zero. Hence the only possible deviations are upwards. Furthermore, the loss associated with a deviation if the opponent plays Nash is zero, and the equilibrium strategy is indeed a weakly dominated strategy. Hence, in the presence of noise, a rational player will not play zero, but set a strictly higher price. Furthermore, as there is a strong strategic complementarity in the price setting behavior of the sellers, this rationalizes why prices may spiral away from zero. For treatment T_2^n , where we also observe strong upward deviations, this argument is less clear, as the expected Nash price is below but close to 1/2. Thus it is not obvious how a rational player will react to noisy play by the opponent. In order to shed more light on the observed deviations from Nash equilibrium we analyze noisy play using the concept of quantal response equilibrium (QRE).

¹⁴Recall that the equilibrium support is $p \in [50, 100]$ for T_1^n , $p \in [20, 100]$ for T_2^n , and $p \in [75, 100]$ for T_1^c . If the competitor sets a price below the minimum of the support the best response is to set a price of 100.

QRE has been successfully applied in the experimental literature to rationalize deviations from Nash outcomes in various games.¹⁵ We isolate the effect of noise on seller's strategies by taking optimal play in the buyers' sub-game as given. Our aim is twofold: First, we investigate to what extent QRE can capture the deviations from theory with respect to average prices and price distributions. Second, following Goeree and Holt (2001), we use the QRE concept to measure the sensitivity of the Nash equilibrium with respect to noise. Our conjecture with respect to this second goal is that market settings with a steeper best response function and larger associated relative profit gains are more likely to be sensitive to the introduction of noise.

The structural approach to QRE, first introduced by McKelvey and Palfrey (1995), is based on a random payoff model, where the profit π of a seller *i*, given the other seller's cumulative distribution function for pricing strategies, F_{-i} , is perturbed by a random error: $\hat{\pi}_i(p, F_{-i}) = E_{p_{-i}}\pi_i(p, F_{-i}) + \epsilon_{i,p}$.¹⁶ Each player assigns a probability to a given action equal to the probability that this action is a best response given the error. The resulting quantal responses can thus be interpreted as noisy best responses. Equilibrium requires players' beliefs about the opponents mixing probabilities to be correct. While this equilibrium requirement puts high demands on the rationality of the players if taken literally, the resulting rule for the mixing probabilities is very intuitive: the probability of choosing an action increases with its expected payoff.

We assume a Gumbel distribution for the error, i.i.d. across actions and players, leading to the logistic form of the quantal response. In our symmetric case the quantal responses are given by the (identical) distribution function over strategies for each seller, $F^Q(p)$, that solves the following functional fixed point:

$$F^{Q}(p) = \int_{0}^{p} exp(\frac{1}{\mu}E\pi_{i}(p, F^{Q}(x)))dx / \int_{0}^{100} exp(\frac{1}{\mu}E\pi_{i}(p, F^{Q}(x)))dx , \forall p \in [0, 100],$$

where $\mu > 0$ is the parameter governing noisiness.¹⁷ With the logistic specification we follow the majority of the experimental literature, making our findings comparable. This specific choice of distributional form, together with the restriction that all treatments are estimated with the same noise, puts discipline on the resulting QRE which depends only on one free parameter, μ .¹⁸ When μ approaches infinity, all prices are equally likely, which can be interpreted as completely noisy strategies. On the other extreme, if μ goes to zero, the quantal response approaches the best response of the underlying pricing game, and behavior converges to a Nash equilibrium.

To judge whether QRE can rationalize the data we fit the QRE cumulative distribution functions of posted prices to the corresponding CDFs in the data by choosing a common μ to minimize the sum of squared deviations.¹⁹ We follow Goeree, Holt, and Palfrey (2003) and normalize the

¹⁵See Goeree, Holt, and Palfrey (2008) for a brief review. An application of QRE to a Bertrand market is given in Baye and Morgan (2004). Two alternative approaches are the ε -Equilibrium concept by Radner (1980) and the introduction of "noise traders" (De Long, Shleifer, Summers, and Waldmann (1990)) who set prices according to a given (exogenous) distribution. We have utilized the latter concept but found that it does not explain the data as well as the QRE (our results are available on request). See also the partial approach to noise trading in the context of the Bertrand model in Dufwenberg and Gneezy (2000).

¹⁶See McKelvey and Palfrey (1995) for the details of the definition and the derivation of the logit specification. Alternatively, QRE can be defined in an axiomatic way, see Goeree, Holt, and Palfrey (2005).

¹⁷We use the reciprocal value of the noise parameter λ often used in the literature, i.e $\lambda \equiv \frac{1}{\mu}$.

 $^{^{18}}$ See Haile, Hortaçsu, and Kosenok (2008) for a discussion of the issue of falsifiability of QRE.

¹⁹We follow the approach by Baye and Morgan (2004). The more standard maximum likelihood estimation is not suitable in our case as in some treatments the density of the QRE distribution approaches zero for part of the support of the empirical distribution. For our purposes there is otherwise no difference between the procedures.

maximum possible payoffs in treatments $T_1^n - T_3^n$ (which is 300) to 100 to obtain the same payoff range in all treatments. Table 7 reports the parameter estimate and the implied expected prices for simultaneously fitting μ , the average distance, the implied distances treatment-by-treatment, as well as the corresponding distances between the theoretical distributions and the data. Figure 5 displays the implied CDFs together with distributions from data and theory.

Table 7: QRE estimates	with con	mmon n	loise par	ameter			
Treatment	T_1^n	T_2^n	T_3^n	T_1^c	T_2^c	T_3^c	
μ			0.062				
Expected QRE price	71.5	53.4	36.9	85.2	70.6	64.0	
Average distance QRE and data			0.7	714			
Distance QRE and data by treatment	0.489	0.593	0.479	0.966	0.329	1.429	
Expected Nash price	69.3	40.2	0.0	86.3	66.7	72.7	
Distance Nash and data by treatment	0.799	1.409	5.358	1.083	1.691	1.621	

Minimized distances between the c.d.f.s of QRE and data (square root of the sum of squared deviations) estimated on a grid of integer prices. When distance is measured as an average over treatments, each treatment receives the same weight. Payoffs in the treatments without capacity constraints (n) are scaled by factor 1/3.

As can be seen, fitting the QRE distributions allows us to match both the expected prices and price distributions of the data quite well, with the exception of treatment T_3^c where the expected price is not well matched. However, in all treatments, the CDF of the QRE fits the data (individually and on average) better than the CDF implied by Nash-equilibrium. As a consequence, the QRE estimates capture well the large deviations of the average prices in treatments T_2^n and T_3^n , while staying close to the equilibrium distributions in the remaining treatments. Furthermore, QRE rationalizes the observed price distributions in the treatments where the Nash equilibrium predicts only point prices (i.e. T_3^n , T_2^c , and T_3^c).²⁰

Another way to see this is by comparing the observed CVs and the CVs implied by the QRE. Such a comparison reveals a remarkably tight fit, taking into account that the QRE is estimated with a common noise parameter for all six treatments. In particular, the CVs implied by the QRE indicates that the QRE capture the observed prices well both in treatments with Nash point prices and in treatments with Nash price distributions. Details are provided in the online appendix 6.5.1.

Result 7 [Seller behavior I] The QRE distributions and expected prices match well the empirical distributions of T_1^n to T_2^c and roughly match the distribution for T_3^c and can thereby rationalize the observed price dispersion in treatments T_3^n , T_2^c and for T_3^c . Furthermore, the QRE estimates account well for the substantial deviations from Nash equilibrium in treatments T_2^n and T_3^n . Finally, the coefficients of variation of the QRE distributions closely match the observed coefficients of variation.

The QRE estimates are the result both of the added noise to individual best responses and equilibrium interaction. To better see the direct effect of noise across treatments we consider two additional exercises. First we analyze a scenario where one player noisily best responds to a player that plays the Nash equilibrium strategy. Second, we study the effect of noise close to the Nash equilibrium.

First, we consider the noisy response of a seller if the opponent plays his Nash equilibrium strategy, given the estimated noise parameter $\mu = 0.062$. That is, for each treatment we characterize

 $^{^{20}}$ In section 6.5 of the appendix we also display the CDFs of the QRE estimated treatment by treatment.



Figure 5: QRE distributions (solid black), theoretical distributions (dashed red) and actual posted price distributions (blue dots) and corresponding average prices indicated by the vertical lines.

the distribution

$$\tilde{F}(p) = \int_{0}^{p} exp(\frac{1}{\mu}E\pi_{i}(p,F(x)))dx / \int_{0}^{100} exp(\frac{1}{\mu}E\pi_{i}(p,F(x)))dx , \forall p \in [0,100]$$

where F(x) is the Nash equilibrium strategy in a given treatment. $\tilde{F}(p)$ captures the direct effect (or first round effect) of noise given that the opponent plays his Nash equilibrium strategy.²¹ The density of $\tilde{F}(p)$, together with its expected value and the expected Nash price, is given in the online appendix 6.5.2 for all six treatments. The deviation is enormous in the Bertrand case, where the expected noisy price response is 50 while the Nash price is 0. The reason is that when playing against the Nash strategy (p = 0), the pay-off is zero for all choices of p. Furthermore, also in T_2^n , the expected price with noise is substantially higher than the expected Nash price. For the other treatments however, the differences between the expected Nash prices and the expected noisy

²¹Let Γ denote the QRE mapping so that $\tilde{F}(p) = \Gamma F(x)$. Then the QRE distribution F^Q is a fixed-point of Γ , $F^Q = \Gamma F^Q$ Let $\Gamma^k(F(x))$ denote the mapping performed k times. Then $F^Q = \lim_{k \to \infty} \Gamma^k F(x)$ provided that the limit exists.

responses are small. Thus, the deviations in the "first round" carry over to the ones we find for the estimated QREs.

Second, we conduct a reversed exercise in which we measure the sensitivity to noise when starting at the Nash equilibrium and then move to QRE with a low value of μ . Table 8 reports the relative and absolute change in the expected price when changing μ from 0 to .01. It reveals that the expected prices diverge from the Nash equilibrium at a substantially lower rate when sellers are capacity constrained than when they are not. Moreover, the absolute values of the price elasticities with respect to noise are increasing in the number of informed buyers for both the unconstrained and the constrained treatments. Note that both the relative and the absolute price changes are highest in T_3^n and T_2^n where observed deviations from the Nash equilibrium are most pronounced.

Table 8: Absolute and relative (percentage) changes in QRE expected price.

Treatment	T_1^n	T_2^n	T_3^n	T_1^c	T_2^c	T_3^c
Relative change	2.48	10,0	∞	0.81	1.42	1.96
Absolute change	1.719	4.025	16.010	0.695	0.944	1.423

Relative (percentage) and absolute changes in expected price when moving from Nash equilibrium ($\mu = 0$) to QRE equilibrium ($\mu = 0.01$). All numbers are absolute values.

Result 8 [Seller behavior II] 1. The "first round" effects of noise on best responses are strong in treatments T_2^n and T_3^n . Thus, the direct effects of noise seem to carry over to the deviations found in the estimated QREs. 2. The unconstrained treatments react more strongly to an increase in noise (μ) when starting at a level of μ close to zero. For both the constrained and the unconstrained treatments the expected QRE price responds more strongly to an increase in μ when the number of informed buyers is higher.

In summary, the QRE analysis confirms our intuition coming from the best responses which suggests that the capacity constrained treatments should be less sensitive to noisy play, despite being computationally more complex.

Finally, an alternative possibility to explain the large deviations is collusive behavior. Evidence of collusive behavior has been documented in a number of market experiments.²² One may think that the complementarity in pricing would give strong incentives to cooperate.²³ However, there are two countervailing forces at play in our experiment. First, sellers are constantly re-matched within a block, which makes it very difficult to establish and maintain a tacit agreement to collude. In line with this Orzen (2008) finds that prices are close to the Nash equilibrium in duopolies resembling the setup in T_1^n and T_2^n if subjects are randomly re-matched from period to period, while prices deviate substantially upwards if subjects stay in the same markets. A similar point is made in Ochs (1990) for a more general setting in which capacity constraints create coordination problems.

²²E.g. Douglas D. Davis (1994) find strong evidence of supra-competitive pricing in Bertrand competition with heterogeneous sellers, and Friedman, Huck, Oprea, and Weidenholzer (2015) find strong evidence of long run collusive behavior for both Cournot duopolies and triopolies. In Douglas D. Davis (1994) subjects stay in the same group over the course of the experiment. In Friedman, Huck, Oprea, and Weidenholzer (2015) subjects play for 1200 periods, and are re matched into new groups after each block of 400 periods.

 $^{^{23}}$ Potters and Suetens (2009) find that collusion in the sense of supra-competitive prices is more often observed when there are strategic complements than when there are strategic substitutes. They compare treatments with complements and substitutes rather than changing the degree of complementarity in a setting with continuous payoff functions and fixed pairs of subjects over many rounds.

Second, in treatments T_2^n and T_3^n where we observe the largest deviations from equilibrium there are also strong incentives to undercut the opponent's price, making successful collusion unlikely.

In Appendix 6.5.4 we analyze our data with respect to collusion. In particular we look for simple arrangements, such as constant prices and uncomplicated rotation schemes, by investigating descriptive statistics of levels and variation in prices and profits. We also follow Friedman, Huck, Oprea, and Weidenholzer (2015) in plotting the probability of a price change in the current period against the price in the previous period. Finally, we perform analysis of end-game effects. We do not find support for collusive behavior in any of these analysis. Furthermore, our indicators suggest that, if anything, coordinating behavior seems to be the least pronounced in treatments T_2^n and T_3^n .

Comparison to previous experiments. How do our results compare to previous studies?²⁴ In our treatments with capacity constraints we test for equilibria in which buyer-coordination is not permitted. Cason and Noussair (2007) (hereafter CN) investigate small experimental markets (a two-seller, three-buyer treatment; and a three-sellers, two-buyer treatment) to test the Burdett, Shi, and Wright (2001) model against the large market model of Montgomery (1991). Their study is based on a design very close to our T_3^c . In their two-seller, three buyer treatment CN find average posted prices of 83.7 for periods 39-48.²⁵ 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.²⁶

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.²⁷ They run their T_3^c treatment for 20 periods. Averaging posted prices over all periods, AF undershoot the equilibrium value by 13.5 percentage points.²⁸ 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.²⁹

AFs study is concurrent and independent to ours. They also examine a treatment similar to

²⁴The following is an incomplete list of experimental studies of market environments that relate to our study. 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. Deck and Wilson (2006) investigate an environment in which sellers have the ability to track customers and offer discriminatory prices based on observed history. There is also a large literature on posted offer markets in which buyers enter the market in a random order, see Ketcham, Smith, and Williams (1984), Douglas D. Davis (1994) and the surveys in chapter 6-8 of Plott and Smith (2008). Since buyers enter in a random order and make their purchases one at a time, there can be no coordination frictions in these markets. Also, in much of this literature sellers are heterogeneous. In a Bertrand setting, seller heterogeneity seems to drive prices down towards the competitive level.

 $^{^{25}}$ After behavior has stabilized, but before the end game effects set in.

²⁶To see this, compare the dynamic regressions in the appendix of this paper with those in CN.

²⁷AF 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.

²⁸Average 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)).

²⁹Compare our Figure 4 with Figure 4 in CN and Figure 4 in AF.

our T_2^c . In contrast to us they fail to find support for Lester's paradox. Their interpretation 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 the first 10 rounds of play.³⁰ 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.

Morgan, Orzen, and Sefton (2006) (hereafter MOS) test the Varian (1980) model, in which sellers are not constrained. Their design differs from ours in a number of ways.³¹ 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.³²

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) duopoly 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.³³ Buyers and sellers were humans, the experiment lasted for 25 periods, and was computerized. Buyer valuations were set at 120 and marginal costs at 0. Re-scaled 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.

³⁰This 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.

³¹Among 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.

 $^{^{32}}$ 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).

³³The 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 .

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 counter-intuitive prediction of Lester's paradox. In addition, our experiment demonstrates 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 can rationalize the observed price choices.

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6 Online Appendix

6.1 Details of the Theoretical Predictions

In the following we give more details of the different market settings and provide some calculations.³⁴ For easier reference we repeat the description of the environment already given in Section 2.

The economy is populated by an integer number of $S \ge 2$ sellers and $B \ge 1$ buyers, all of which are risk neutral. Buyers have a unit demand with a reservation price normalized to one. The model consists of two stages: First, sellers simultaneously set prices $p_s \in [0, 1]$.³⁵ 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 $U \ge 0$ of uninformed buyers independently and randomly choose a seller, where each seller is visited with equal probability. Further, there are $N \ge 1$ informed buyers who can costlessly observe all prices offered in the market and choose at which seller to buy. We assume a fixed number of buyers, so that we can infer the number U = B - N. With respect to capacity we consider two cases. In the first case (z = c) sellers are capacity constrained and have only one unit on hand, whereas in the second case (z = n) firms are not capacity constrained, and each firm has B units for sale.

The expected payoff of a seller s is $\pi_s^{z,N}(p_s, p_{-s}) = \mu^{z,N}(p_s, p_{-s})p_s$, where $\mu^{z,N}(p_s, p_{-s})$ is the expected number of sales given the number of units in stock (z), the number of informed buyers (N), the own price and the prices of other sellers. The expected payoff of a buyer *i* conditional on choosing a seller s is $v_i^{z,N}(\theta_{-i}^s) = \eta^{z,N}(\theta_{-i}^s)(1-p_s)$, where $\eta^{z,N}(\theta_{-i}^s)$ is the probability of getting the good at seller s given that the other buyers go to this seller with probabilities θ_{-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.

Equilibria with no Capacity Constraints. We first look at the case where there are at least some uninformed buyers, $U \ge 1$. 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 $\mu^{n,N}(p_s, p_{-s}) = N + U/S$ if p_s is the lowest price and $\mu^{n,N}(p_s, p_{-s}) = U/S$ otherwise.³⁶ One can show that the symmetric equilibrium entails a mixed strategy given by the c.d.f. F(p) with support $p \in [p_0, 1]$.³⁷ 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): $\int \pi_s^{n,N}(p_s, p_{-s}) dF(p_{-s}) = \int \pi_s^{n,N}(1, p_{-s}) dF(p_{-s})$. This can be written as:

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

 $^{^{34}}$ For a more in-depth treatment we refer the reader to the articles by Varian (1980), Burdett, Shi, and Wright (2001), and Lester (2011).

³⁵Here we normalize the price range to the unit interval for convenience.

³⁶It 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.

³⁷The 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.

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:

$$F(p) = 1 - \left(\frac{1-p}{p}\frac{U}{SN}\right)^{1/(S-1)}$$
 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:

$$E[p] = p_0 + \int_{p_0}^1 (1 - F(p)) dp$$

= $p_0 + \int_{p_0}^1 \left(\frac{1 - p}{p} \frac{U}{SN}\right)^{1/(S-1)} dp.$ (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 cumulative distribution function of the lowest price in the market is given 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 θ^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 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 $m \equiv \mu^{c,1}(1, p_{-s}) = 1 - (1 - 1/S)^U$ 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:

$$F(p) = 1 - \left(\frac{m}{1-m}\frac{1-p}{p}\right)^{\frac{1}{S-1}}$$
, 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 uninformed 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:³⁸

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

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, $v_i^{c,N}(\theta_{-i}^{s'}) = v_i^{c,N}(\theta_{-i}^{s''})$ 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:

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

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

$$\max_{p_s} \mu^{c,N}(p_s, p_{-s}^*) p_s$$

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: $\eta^{c,N}(\theta^s)(1-p_s) = \eta^{c,N}((1-\theta^s)/(S-1))(1-p^*)$. 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:

$$p^* = M/[M + (1 - \mu(p^*, p^*))\eta(1/S)\{N(B - 1)/(S(N - 1))\}],$$
(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.: $\mu(p^*, p^*)p^* \ge \mu(1, p^*) \cdot 1$. This condition is satisfied for the parameters of our treatments.

³⁸This follows from the binomial distribution.

6.1.1 Calculations for the expected posted and transaction prices

In the following we set S = 2 and B = 3, with N > 0 and provide details of the calculations for the expected posted and transaction prices given in Table 1.

First, for the case without capacity constraints and 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 1.

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

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

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 $E[p_T] = \frac{2\cdot3/4\cdot1}{7/4} = 6/7 \approx .857$.

6.1.2 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:

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

6.2 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 β_{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 β_{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 β_{i2} is closer to the equilibrium value of the treatment than is β_{i1} .

convergence if β_{i2} is closer to the equilibrium value of the treatment than is β_{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 : $\beta_2 = equilibrium$ 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 $\bar{t} = 48$.³⁹ Table 9 provides the estimates for posted prices with the first specification, Table 10 provides the estimates for posted prices with the second specification.

From Table 9 we observe that for treatments T_1^c to T_3^c each β_{i2} term is closer to the equilibrium price than its corresponding β_{i1} term. In treatments T_1^n to T_3^n a slim majority - three of five - β_{i2} terms are closer to equilibrium than their corresponding β_{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 β_{i2} terms are equal can be rejected with high degree of certainty. Thus, convergence is not strong in any treatment.

Next, consider Table 10. Except for treatments T_2^n to T_3^n , the estimate of β_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 β_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

³⁹The 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).

Tr	β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	β_{21}	β_{22}	β_{23}	β_{24}	β_{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)		

 Table 9: Convergence regressions

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

in all five matching blocks, as shown in Table 11. Qualitatively, the regressions are consistent with posted prices converging to a common value in these treatments. However, the null that $\beta_{21} = \beta_{22} = \ldots = \beta_{25}$ cannot be rejected with any degree of confidence.

Tr	β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	β_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)		

Table 10: Equilibrium convergence

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

	β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	β_{21}	β_{22}	β_{23}	β_{24}	β_{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)	

Table 11: Variance in posted prices

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

6.3 Treatment regressions

Table 12 reports GLS regressions of prices on treatment dummies with random effects for individual sellers. Standard errors are clustered on unique blocks to correct for heteroscedasticity. In regressions labeled PP the dependent variable is the posted price, while in regressions labeled TPthe dependent variable is the transaction price.

		2. 11		Cgrue				
	PPI	***	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)			
$T_2^n \cdot \text{Period}$	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	
\mathbb{R}^2	0.45		0.43		0.52		0.52	
F-stat	50.8	***	91.4	***	80.4	***	144.5	***

Table 12: Treatment regressions

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. 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.

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 that the coefficient of T_2^c is larger than or equal to that of T_3^c with a *p*-value of 0.124 for posted prices, and with a *p*-value of 0.093 for transaction prices. Hence the null hypothesis that prices cannot be formally rejected at a 10% significance level using posted prices, while it is comfortably rejected at the 10% significance level using transaction prices. Thus, regressing prices on treatment dummies and a time trend lends further support to Lester's paradox.

In sum: 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. Due to the presence of dispersion in posted prices. In Section 4 of the paper, we investigate this deviation from theory by hypothesizing noisy responses on the seller side.

6.4 Buyer behavior

Figure 6.4 shows the fraction of buyers visiting seller square in 20 bins of length 0.05 on the theoretical probability of such an action. Lines display a 95% confidence interval for the error of the mean in each bin. The null hypothesis is that the mean is located on the 45-degree line. For treatment T_2^c we are unable to reject this null in 17 out of 20 bins at a 5% significance level. For treatment T_3^c we are unable to reject the null in 15 out of 20 bins at this level of significance.



Figure 6: 95 % confidence intervals around the mean buyer reaction in 20 bins of length 0.05 for treatments T_2^c and T_3^c .

6.5 Seller behavior

6.5.1 Coefficients of variation implied by QRE

Table 13 shows the coefficients of variation implied by the QRE estimated with a noise of $\mu = 0.062$. For ease of comparison the coefficients of variation calculated on the basis of the data are included.

Table 13: Coefficients of variation implied by QRE and based on data.

Treatment	T_1^n	T_2^n	T_3^n	T_1^c	T_2^c	T_3^c
CVs implied by QRE	0.24	0.38	0.55	0.12	0.18	0.15
CVs based on data	0.27	0.48	0.55	0.15	0.17	0.17

6.5.2 Best response with noise

Figure shows the noisy best response to the opponent playing the equilibrium Nash strategy for noise parameter $\mu = 0.062$.



Figure 7: Noisy best response to Nash strategy. Solid (red) line is the (discrete) probability distribution of the noisy best response (for a grid of 1001 price points); the dashed (red) line the expected probability; the dotted (blue) line the expected Nash equilibrium price. Noise parameter is $\mu = 0.062$.

6.5.3 QRE estimates with individual noise parameter

In Table 14 we report the results of fitting μ_N^z treatment by treatment (see Figure 8 for the corresponding distribution graphs).

Treatment	T_1^n	T_2^n	T_3^n	T_1^c	T_2^c	T_3^c
μ_N^z	0.086	0.038	0.083	0.046	0.054	0.022
Expected price	69.8	50.7	40.3	86.1	70.1	69.5
Distance	0.412	0.482	0.170	0.943	0.289	1.023

Table 14: Individual QRE estimates



Figure 8: QRE distributions (solid black), theoretical distributions (dashed red) and actual posted price distributions (blue dots) and corresponding average prices indicated by the vertical lines for the case of individually fitted μ_N^z .

6.5.4 Testing for collusion

In the following we consider several heuristic indicators to evaluate whether or not the large deviations from Nash equilibrium in treatments T_2^n and T_3^n can be rationalized by tacit collusion. There is a substantial experimental literature on collusion in oligopoly models building on the seminal

Minimum average distance (square root of the sum of squared deviations) estimation on a grid of integer prices. Payoffs in the treatments without capacity constraints (n) are scaled by factor 1/3.

contribution by Davis and Holt (1996). Most experimental tests use a fixed matching of subjects. As sellers in our case are randomly re-matched we conjecture that tacit collusion in the sense of coordination on above-equilibrium prices will be very difficult to accomplish.⁴⁰ Unfortunately, there seems to be no consensus on what behavior identifies such coordination. The most common operational definition of collusion is therefore the occurrence of a supra-competitive price (see e.g. Davis, Korenok, and Reilly (2010) and Potters and Suetens (2009)). As we claim that noisy play can also lead to supra-competitive prices we need to explicitly analyze behavior to distinguish these different explanations.

A recent study of collusive behavior is Friedman, Huck, Oprea, and Weidenholzer (2015). They run 1200 period of an oligopoly game. Subjects stay in a partner matching for 400 periods, and are re-matched twice. Among other things they test for imitating rules based on current and past behavior of the opponent. With random re-matching in each new period - as in our experiment such imitation becomes very difficult. We concur with Kruse, Rassenti, Reynolds, and Smith (1994) that feasible schemes of tacit collusion should not go beyond simple patterns such as constant prices or simple rotation schemes. In the following we check several statistics which we believe are informative about collusive behavior. One advantage of our design is that we can compare these indicators to the treatments that are close to the equilibrium predictions and for which we therefore expect a lower degree of collusion, if any at all.

First we check how often sellers individually set the joint profit maximizing price, which is to set p = 100 (see first row of Table 15). As expected, both in the treatments with and without capacity constraints this share is decreasing in N. Second, the overall share is quite low (6.6 % on average). Third, and most importantly, this share is below average for treatments T_2^n and T_3^n . Furthermore, only few of these individual maximum price decisions resulted in the joint profit maximum (JPM) as the next row of the table shows. In fact, there are virtually no occurrences of a JPM for treatments T_2^n and T_3^n .

	T_1^n	T_2^n	T_3^n	T_1^c	T_2^c	T_3^c
Share of $p = 100$.061	.043	.013	.251	.022	.003
Share of $p_T = 100$.008	.001	.000	.068	.000	.000
Share of equal prices	.025	.021	.016	.087	.040	.061
Repeated prices by subject	.158	.267	.128	.344	.411	.433
Repeated prices by market	.125	.101	.059	.276	.153	.171
SD of prices by market	17.0	23.2	20.5	11.7	11.3	11.1
CV of total profits within blocks	.082	.160	.218	.068	.088	.069

Table 15: Heuristic indicators of collusive behavior

Instead of playing the optimal cooperative strategy, players could simply try to increase profits by coordinating on an arbitrary price (that yields higher profits than the Nash equilibrium payoffs). In the third row of Table 15 we report the proportion of equal prices, averaged over all markets and periods for a given treatment. In the treatments with large deviations $(T_2^n \text{ and } T_3^n)$ this share is very low on average (below 2%). Moreover, it turns out that it is also much lower than in the other treatments (where it is above 5% on average).

 $^{^{40}}$ Explicit tests for the influence of the matching schemes has found significant effects on outcomes. See Orzen (2008) for an analysis of a Varian-type model and Huck et al. (2001) and Davis et al. (2010) for other oligopoly models.

Next, we analyze whether sellers attempt to signal a price to coordinate on by repeating the same price twice in a row.⁴¹ The fourth row of Table 15 shows price repetitions as a share of all prices set by a subject within a block (averaged over all sellers within a treatment). As subjects switch markets frequently this translates into a much lower rate when computing the share of repeated prices for a given market as the subsequent row in the table shows. (price repetitions then can either be caused by a single subject or accidentally). What is noteworthy is that price repetitions occur at a lower rate in treatments T_2^n and T_3^n compared to the average over all treatments. This is also reflected in the larger standard deviation of prices for a given market and seller name for these two treatments. That is, prices fluctuate more in these treatments, which is likely to be due to the "strong" discontinuity of demand in these treatments. Thus, there is no indication of a particularly intense signaling activity for the large deviation treatments. Relatedly, we draw on the analysis in Friedman, Huck, Oprea, and Weidenholzer (2015) and check whether price changes are systematically related with the current price. Figures 9 and 10 display the stability of prices by plotting the probability of a posted price being changed in the current period as a function of the price posted in the previous period. Each point in the figures represents the average probability of a price change in the current period given a posted price in the previous period from bin [0-10), [10-20), ..., [90-100]. The radius of the circles are proportional to the number of sellers having posted a price in the relevant bin in the previous period. Figure 9 aggregates over all 50 periods of the experiment, Figure 10 aggregates over the last 25 periods of the experiment (when sellers presumably have had ample time to learn how to collude).

Consider first T_3^n . Most prices in the previous period fall in the range 30 - 60 and the probability of a price change in the current period is very high for any price posted in the previous period. There is no sign that posted prices converge towards a specific price bin. The picture remains largely unchanged whether we consider all periods or only the last 25 periods.

In T_1^n , T_2^n and T_1^c sellers should randomize over a price support in equilibrium. In these treatments the mass of observations lie in the support of the equilibrium strategy and the probability of a price change in the current period is high for any price posted in the previous period.

In T_2^n most posted prices lie in the bin [30 - 40) (i.e. close to the expected equilibrium price) while the probability of a price change is at its minimum for posted prices in the bin [20-30). Higher prices are more volatile. Clearly, posted prices are not converging to a single bin, indicating that the substantial deviation from equilibrium in T_2^n is not explained by a simple collusive agreement (for instance to coordinate on the observed average price of roughly 50). Again, the picture is broadly unchanged whether we consider all periods or only the last 25 periods.

In T_1^c most prices lie in the bin [90 - 100] and prices are more stable in this bin than in other bins. Very few prices are posted in bins below [70 - 80). The picture is consistent with sellers randomizing on the narrow support of the equilibrium in this treatment.

In T_2^c and T_3^c sellers should set a single price in equilibrium. In these treatments behavior is pushed in the direction of the expected equilibrium prices, and if anything this becomes more pronounced in the last 25 periods of the experiment.

Taken together, the graphs show no sign of effective collusion taking place, in the sense that sellers manage to stabilize prices at some particular level above the equilibrium of the standard model. Investigating corresponding graphs block by block confirms the pattern displayed in Figures 9 and 10 (available upon request).

If sellers were successful in establishing and maintaining a collusive arrangement, the incentive to deviate would become very strong as the experiment progressed towards the end. We therefore

⁴¹See Davis et al. (2010) for a test and a discussion of signaling within an oligopoly framework.



Figure 9: Stability of posted prices treatment by treatment, averaged over the last 25 periods.



Figure 10: Stability of posted prices treatment by treatment, averaged over all periods.

check whether prices fall in the final periods of the experiment.

Table 16 shows the difference between average posted prices in the final period(s) and the immediately preceding period(s). We check for changes in average posted prices between strings of one and up to and including five periods. Only in 4 out of the 30 cases covered by the table do prices decrease, and non of these 4 price decreases are significant at conventional levels in a Wilcoxon signed rank test (using average posted prices of individual sellers as units of observation). In contrast 14 of the 26 price increases are significant at the 10 percent level or better. We interpret this pattern as an indication that collusive arrangements is not likely to explain our data.

Periods	T_1^n		T_2^n		T_3^n	T_1^c		T_2^c		T_3^c	
49 vs. 50	11.0	***	3.1		-3.8	4.9	***	6.8	***	1.3	**
	(.004)		(.517)		(.229)	(.001)		(.005)		(.037)	
47-48 vs. 49-50	8.0	**	4.2	*	2.3	.1		2.3		-1.6	
	(.034)		(.076)		(.667)	(.590)		(.114)		(.504)	
45-47 vs. 48-50	7.3	***	7.9	**	3.0	1.0	*	2.9	*	-0.6	
	(.003)		(.035)		(.453)	(.074)		(.071)		(.827)	
43-46 vs. 47-50	4.5	**	4.3		1.0	.6		3.8	***	.5	
	(.011)		(.253)		(.967)	(.653)		(.006)		(.228)	
41-45 vs. $46-50$	2.9	**	.7		-2.5	.4		2.9	*	0.5	
	(.043)		(.750)		(.125)	(.605)		(.065)		(.344)	

Table 16: Change in posted prices (p-values from Wilcoxon matched pairs tests)

Though we do not believe that sellers are able to coordinate on more sophisticated collusion schemes (e.g. some complicated rotation between sellers of setting high prices), we can compare the total profits at the end of the game to check whether sellers managed to share profits within a block in an equal manner. While a priori any profit distribution could be consistent with collusion it seems intuitive that in our symmetric setting cooperation should entail an equal sharing of profits to some degree. The last row in Table 11 reveals that in fact profits are most unequally distributed within blocks for treatments T_2^n and T_3^n (measured by the coefficient of variation within a block, averaged over all blocks). Thus, cooperation within blocks seems less likely or at least less successful in these treatments.

In summary, our heuristic indicators suggest that coordinated price setting seems less prevalent in those treatments where we would expect it most due to large deviations from the Nash equilibrium outcomes. In particular, sellers in T_2^n and T_3^n almost never achieve the joint profit maximum.

6.6 Instructions and screenshots of experiment

This is an economics experiment, administered by the department of economics at the school.

In economics experiments deception is <u>never</u> used. This means that any information you are provided with in the experiment is <u>correct</u>.

Experiments administered by other departments at the school may use deception. Whenever they do, you are told so.

Instructions

You are going to participate in a session of a market experiment financed by the Department of Economics at BI and the Norwegian Research Council. The session will not last more than 90 minutes.

In the experiment you will earn money. How much you earn depends on the decisions you make, as well as on the decisions made by other subjects.

All interactions are anonymous and are performed through a network of computers. The administrators of the experiment will not be able to observe your decisions during the session.

The people in this room are participating in the same experiment as you. They have all been recruited in the same way as you and are reading the same instructions as you are for the first time. It is important that you do not talk to any of the other participants in the room until the session is over.

The experiment will consist of 50 periods, in each of which you can earn units of an experimental currency that we call "schilling". At the end of the experiment you will be paid based on your total earnings in schillings from all 50 periods.

1 schilling is worth 0.04 Norwegian Kroner.

The more schillings you earn, the more cash you will receive. If you follow the instructions carefully and make good decisions, you can earn a considerable amount of money.

Overview

The experiment consists of a market with sellers and buyers. Each buyer wants to by one unit of a good and each seller has three units of the good to sell. Sellers choose at which price to sell, and buyers choose which seller to buy the good from.

Description of a Period

When the game starts, you will be randomly assigned a type. Your type will be either buyer BLUE or seller CIRCLE or SQUARE. You will retain this type throughout periods 1 to 50.

At the start of each new period, you will be randomly matched with exactly two other human subjects in the room, plus two robot buyers. Robot behavior is explained below. You and these four others form a "market" consisting of exactly two human sellers (CIRCLE and SQUARE), one human buyer (BLUE), and two robot buyers (RED and GREEN). It is unlikely that the same market forms two periods in a row.

Each buyer gets an endowment of 100 schillings at the start of each period. In each period each seller has three units to sell. Buyers can only buy one unit. A period consists of two decision stages.

1. <u>The selling stage</u>: In this stage one the two sellers (CIRCLE and SQUARE) independently post a binding price between 0 and 100 schillings that they are willing to sell their units for. Prices can be entered with two decimals. Make sure to use "." (i.e., dot) as a separator if you are a seller and wish to post a price in decimals.

The human buyer (BLUE) observes the posted prices. The robot buyers (RED and GREEN) do not observe the prices.

2. <u>The buying stage</u>: In this stage each of the buyers decides which of the two sellers to buy their unit from. The robot buyers (RED and GREEN) toss a fair coin independently to determine which buyer to buy from.

Profits

The profit of a buyer in any given period is 100 schillings minus the price offered by the buyer he or she purchases from. Profits are added over all periods.

The profit of a seller in any given period equals the price offered times the items sold at this price. Profits are added over all periods.

Feedback

After transactions have been carried out in any given period, all participants are informed about the profits made by all the participants in the market in that period.

At the end of a period a statistics of the history is displayed. This statistic keeps track of own profits; the prices posted by the two sellers; the choices made by the three buyers; and the queues formed at the two sellers in the current and all previous periods. In addition your accumulated profits (in schillings) are displayed.

Earnings

After period 50 your earnings in schilling are converted to Norwegian Kroner, and paid out in cash as you leave the lab.

Are there any questions?

This is an economics experiment, administered by the department of economics at the school.

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Instructions

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In the experiment you will earn money. How much you earn depends on the decisions you make, as well as on the decisions made by other subjects.

All interactions are anonymous and are performed through a network of computers. The administrators of the experiment will not be able to observe your decisions during the session.

The people in this room are participating in the same experiment as you. They have all been recruited in the same way as you and are reading the same instructions as you are for the first time. It is important that you do not talk to any of the other participants in the room until the session is over.

The experiment will consist of 50 periods, in each of which you can earn units of an experimental currency that we call "schilling". At the end of the experiment you will be paid based on your total earnings in schillings from all 50 periods.

1 schilling is worth 0.04 Norwegian Kroner.

The more schillings you earn, the more cash you will receive. If you follow the instructions carefully and make good decisions, you can earn a considerable amount of money.

Overview

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At the start of each new period, you will be randomly matched with exactly two other human subjects in the room, plus two robot buyers. Robot behavior is explained below. You and these four others form a "market" consisting of exactly two human sellers (CIRCLE and SQUARE), one human buyer (BLUE), and two robot buyers (RED and GREEN). It is unlikely that the same market forms two periods in a row.

Each buyer gets an endowment of 100 schillings at the start of each new period. In each period each seller has a single unit to sell. Buyers can only buy one unit. A period consists of two decision stages.

1. <u>The selling stage</u>: In this stage one the two sellers (CIRCLE and SQUARE) independently post a binding price between 0 and 100 schillings that they are willing to sell their unit for. Prices can be entered with two decimals. Make sure to use "." (i.e., dot) as a separator if you are a seller and wish to post a price in decimals.

The human buyer (BLUE) observes the posted prices. The two robot buyers (RED and GREEN) do not observe the posted prices.

2. <u>The buying stage</u>: In this stage the human buyer (BLUE) decides which of the two sellers to buy from. The robot buyers (RED and GREEN) independently toss a fair coin to determine which of the two sellers to buy from.

If two or more buyers wish to buy from the same seller, a random draw determines which of the buyers in the queue gets the item. Each buyer in a queue has an equal probability of getting the item.

Profits

The profit of a buyer for any given period is 100 schillings minus the price offered if the buyer succeeds in getting the item and 0 schillings if he/she is unsuccessful. That is, a buyer can only earn money in a given period if she or he succeeded in buying a good. Profits are added over all periods.

The profit of a seller for any given period equals the price offered if the item is sold, and 0 schillings if the item is not sold. Profits are added over all periods.

Feedback

After transactions have been carried out in any given period, all participants are informed about the profits made by all the participants in the market in that period.

At the end of a period a statistic of the history is displayed. This statistic keeps track of own profits; the prices posted by the two sellers; the choices made by the three buyers; and the queues formed at the two sellers in the current and all previous periods. In addition your accumulated profits (in schillings) are displayed.

Earnings

After period 50 your earnings in schilling are converted to Norwegian Kroner, and paid out in cash as you leave the lab. Are there any questions?

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Instructions

You are going to participate in a session of a market experiment financed by the Department of Economics at BI and the Norwegian Research Council. The session will not last more than 90 minutes.

In the session you will earn money. How much you earn depends on the decisions you make, as well as on the decisions made by other subjects.

All interactions are anonymous and are performed through a network of computers. The administrators of the experiment will not be able to observe your decisions during the session.

There are XX people in this room who are participating in your session. They have all been recruited in the same way as you and are reading the same instructions as you are for the first time. It is important that you do not talk to any of the other participants in the room until the session is over.

The session will consist of 50 periods, in each of which you can earn units of an experimental currency that we call "schilling". At the end of the experiment you will be paid based on your total earnings in schillings from all 50 periods.

1 schilling is worth 0.08 Norwegian Kroner.

The more schillings you earn, the more cash you will receive.

Overview

The experiment consists of a market with sellers and buyers. Each buyer wants to buy one unit of a good and each seller has three units of the good to sell. Sellers choose at which price to sell, and buyers choose which seller to buy the good from.

Description of a Period

When the experiment starts, you will be designated as either buyer BLUE or RED or as seller CIRCLE or SQUARE. You will retain this type throughout periods 1 to 50.

At the start of each new period, you will be randomly matched with exactly three other human subjects in the room, plus a robot buyer. Robot behavior is explained below. You and these four others form a "market" consisting of exactly two human sellers (CIRCLE and SQUARE), two human buyers (BLUE and RED), and one robot buyer (GREEN). It is unlikely that the same market forms two periods in a row.

Each buyer gets an endowment of 100 schillings at the start of each period. In each period each seller has three units to sell. Buyers can only buy one unit. A period consists of two decision stages.

<u>The selling stage</u>: in this stage (stage one) the two sellers (CIRCLE and SQUARE) independently
post a binding price between 0 and 100 schillings that they are willing to sell their units for.
Prices can be entered with two decimals. Make sure to use "." (i.e., dot) as a separator if you are
a seller and wish to post a price in decimals.

The human buyers (BLUE and RED) observe the posted prices. The robot buyer (GREEN) does not observe the prices.

2. <u>The buying stage</u>: In this stage (stage two) each of the buyers decides which of the two sellers to buy their unit from. The robot buyer (GREEN) tosses a fair coin to determine which buyer to buy from.

Profits

The profit of a buyer in any given period is 100 schillings minus the price paid.

The profit of a seller in any given period equals the price offered multiplied by the number of items sold (if no items are sold the profit is 0 schillings).

Profits are added over all periods.

Feedback

After transactions have been carried out in any given period, all participants are informed about the profits made by all the participants in their market in that period.

At the end of a period a historical statistic is displayed. This statistic keeps track of own profits; the prices posted by the two sellers; the choices made by the three buyers; and the queues formed at the two sellers in the current and all previous periods. In addition your accumulated profits (in schillings) are displayed.

Earnings

After period 50 your earnings in schilling are converted to Norwegian Kroner and paid out in cash as you leave the lab.

Are there any questions?

This is an economics experiment, administered by the department of economics at the school.

In economics experiments deception is <u>never</u> used. This means that any information you are provided with in the experiment is <u>correct</u>.

Experiments administered by other departments at the school may use deception. Whenever they do, you are told so.

Instructions

You are going to participate in a session of a market experiment financed by the Department of Economics at BI and the Norwegian Research Council. The session will not last more than 90 minutes.

In the session you will earn money. How much you earn depends on the decisions you make, as well as on the decisions made by other subjects.

All interactions are anonymous and are performed through a network of computers. The administrators of the experiment will not be able to observe your decisions during the session.

There are XX people in this room who are participating in your session. They have all been recruited in the same way as you and are reading the same instructions as you are for the first time. It is important that you do not talk to any of the other participants in the room until the session is over.

The session will consist of 50 periods, in each of which you can earn units of an experimental currency that we call "schilling". At the end of the experiment you will be paid based on your total earnings in schillings from all 50 periods.

1 schilling is worth 0.04 Norwegian Kroner.

The more schillings you earn, the more cash you will receive. If you follow the instructions carefully and make good decisions, you can earn a considerable amount of money.

In addition to the money earned each subject will receive a show up fee of 100 Norwegian Kroner.

Overview

The experiment consists of a market with sellers and buyers. Each buyer wants to buy one unit of a good and each seller has one unit to sell. Sellers choose at which price to sell, and buyers choose which seller to buy the good from.

Description of a Period

When the experiment starts, you will be randomly assigned a type. Your type will be either buyer BLUE or RED, or seller CIRCLE or SQUARE. You will retain this type throughout periods 1 to 50.

At the start of each new period, you will be randomly matched with exactly three other human subjects in the room, plus one robot buyer. Robot behavior is explained below. You and these four others form a "market" consisting of exactly two human sellers (CIRCLE and SQUARE), two human buyers (BLUE and RED), and one robot buyer (GREEN). It is unlikely that the same market forms two periods in a row.

Each buyer gets an endowment of 100 schillings at the start of each period. In each period each seller has a single unit to sell. Buyers can only buy one unit.

1. <u>The selling stage</u>: In this stage (stage one) the two sellers (CIRCLE and SQUARE) independently post a binding price between 0 and 100 schillings that they are willing to sell their unit for. Prices can be entered with two decimals. Make sure to use "." (i.e., dot) as a separator if you are the seller and wish to post a price in decimals.

The human buyers (BLUE and RED) observe the posted prices. The robot buyer (GREEN) does not observe the posted prices.

2. <u>The buying stage</u>: In this stage (stage two) the human buyers (BLUE and RED) decides which of the two sellers to buy from. The robot buyer (GREEN) tosses a fair coin to determine which of the two sellers to buy from.

If two or more buyers wish to buy from the same seller, a random draw determines which of the buyers in the queue gets the item. Each buyer in a queue has the same probability of getting the item.

Profits

The profit of a buyer in any given period is 100 schillings minus the price offered if the buyer succeeds in getting the item and 0 schillings if he/she is unsuccessful.

The profit of a seller in any given period equals the price offered if the item is sold, and 0 schillings if the item is not sold. Profits are added over all periods.

Feedback

After transactions have been carried out in any given period, all participants are informed about the profits made by all the participants in the market in that period.

At the end of a period a historical statistic is displayed. This statistic keeps track of own profits; the prices posted by the two sellers; the choices made by the three buyers; and the queues formed at the two sellers in the current and all previous periods. In addition your accumulated profits (in schillings) are displayed.

Earnings

After period 50 your earnings in schilling are converted to Norwegian Kroner, added to the show up fee, and paid out in cash as you leave the lab.

Are there any questions?

This is an economics experiment, administered by the department of economics at the school.

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Experiments administered by other departments at the school may use deception. Whenever they do, you are told so.

Instructions

You are going to participate in a session of a market experiment financed by the Department of Economics at BI and the Norwegian Research Council. The session will not last more than 90 minutes.

In the session you will earn money. How much you earn depends on the decisions you make, as well as on the decisions made by other subjects.

All interactions are anonymous and are performed through a network of computers. The administrators of the experiment will not be able to observe your decisions during the session.

There are 30 people in this room who are participating in your session. They have all been recruited in the same way as you and are reading the same instructions as you are for the first time. It is important that you do not talk to any of the other participants in the room until the session is over.

The session will consist of 50 periods, in each of which you can earn units of an experimental currency that we call "schilling". At the end of the experiment you will be paid based on your total earnings in schillings from all 50 periods.

1 schilling is worth 0.05 Norwegian Kroner.

The more schillings you earn, the more cash you will receive.

All participants get a show up fee of 175 Norwegian Kroner in addition to whatever they earn in the experiment.

Description of a Period

At the start of period 1 you will be designated a role. The roles are buyer BLUE, RED or GREEN and seller CIRCLE or SQUARE. You will keep your designated role for the duration of the experiment.

At the start of each new period, you will be randomly matched with exactly four other subjects in the room. You and these four others form a "market" consisting of exactly two sellers (CIRCLE and SQUARE) and three buyers (BLUE, RED and GREEN).

Each buyer gets an endowment of 100 schillings at the start of each period. In each period each seller has three units to sell. Buyers can only buy one unit.

A period consists of two decision stages.

In <u>stage one</u> the two sellers (CIRCLE and SQUARE) independently post a binding price between 0 and 100 schillings that they are willing to sell their units for. Prices can be entered with two decimals. Make sure to use "." (a dot sign) as a separator if you are a seller and wish to post a price in decimals.

All three buyers (BLUE, RED and GREEN) observe the posted prices.

In stage two each of the buyers decide which of the two sellers to buy their unit from.

Profits

The profit of a buyer in any given period is 100 schillings minus the price offered if the buyer succeeds in getting the item and 0 schillings if he/she is unsuccessful.

The profit of a seller in any given period equals the price offered for the items sold, and 0 schillings if no items are sold.

Feedback

After transactions have been carried out in any given period, all participants are informed about the profits made by all the participants in the market in that period.

At the end of a period a historical statistic is displayed. This statistic keeps track of own profits; the prices posted by the two sellers; the choices made by the three buyers; and the queues formed at the two sellers in the current and all previous periods. In addition your accumulated profits (in schillings) are displayed.

Earnings

After period 50 your earnings in schilling are converted to Norwegian Kroner, and paid out in cash as you leave the lab.

Are there any questions?

This is an economics experiment, administered by the department of economics at the school.

In economics experiments deception is <u>never</u> used. This means that any information you are provided with in the experiment is <u>correct</u>.

Experiments administered by other departments at the school may use deception. Whenever they do, you are told so.

Instructions

You are going to participate in a session of a market experiment financed by the Department of Economics at BI and the Norwegian Research Council. The session will not last more than 90 minutes.

In the session you will earn money. How much you earn depends on the decisions you make, as well as on the decisions made by other subjects.

All interactions are anonymous and are performed through a network of computers. The administrators of the experiment will not be able to observe your decisions during the session.

There are 45 people in this room who are participating in your session. They have all been recruited in the same way as you and are reading the same instructions as you are for the first time. It is important that you do not talk to any of the other participants in the room until the session is over.

The session will consist of 50 periods, in each of which you can earn units of an experimental currency that we call "schilling". At the end of the experiment you will be paid based on your total earnings in schillings from all 50 periods.

1 schilling is worth 0.1 Norwegian Kroner.

The more schillings you earn, the more cash you will receive

Description of a Period

When the game starts, you will be randomly allocated a type. Your type will be either buyer BLUE, RED or GREEN or seller CIRCLE or SQUARE. You will retain this type throughout periods 1 to 50.

At the start of each new period, you will be randomly matched with exactly four other subjects in the room. You and these four others form a "market" consisting of exactly two sellers (CIRCLE and SQUARE) and three buyers (BLUE, RED and GREEN).

Each buyer gets an endowment of 100 schillings at the start of each period. In each period each seller has a single unit to sell. Buyers can only buy one unit.

A period consists of two decision stages:

In <u>stage one</u> the two sellers (CIRCLE and SQUARE) independently post a binding price between 0 and 100 schillings that they are willing to sell their unit for. Prices can be entered with two decimals. Make sure to use "." (a dot sign) as a separator if you are a seller and wish to post a price in decimals.

All three buyers (BLUE, RED and GREEN) observe the posted prices.

In <u>stage two</u> each of the buyers decide which of the two sellers to buy from. If two or more buyers wish to buy from the same seller, a random draw determines which of the buyers in the queue gets the item. Each buyer in a queue has the same probability of getting the item.

Profits

The profit of a buyer in any given period is 100 schillings minus the price offered if the buyer succeeds in getting the item and 0 schillings if he/she is unsuccessful.

The profit of a seller in any given period equals the price offered if the item is sold, and 0 schillings if the item is not sold.

Feedback

After transactions have been carried out in any given period, all participants are informed about the profits made by all the participants in the market in that period.

At the end of a period a historical statistic is displayed. This statistic keeps track of own profits; the prices posted by the two sellers; the choices made by the three buyers; and the queues formed at the two sellers in the current and all previous periods. In addition your accumulated profits (in schillings) are displayed.

Earnings

After period 50 your earnings in schilling are converted to Norwegian Kroner, and paid out in cash as you leave the lab.

Are there any questions?

Period	1 out of 50	Remaining time [sec]: 75
	RULES	
	1. The market has two sellers - seller CIRCLE and seller SQUARE, and three buyers - buyer GREEN, BLUE and RED	
	2. The two sellers offer binding prices between 0.00 and 100.00 schilling .	
	3. Buyer BLUE is <i>informed</i> about these prices.	
	4. Buyer GREEN and buyer RED are not informed about the prices of the sellers.	
	5. All buyers make their purchase decisions .	
	6. Buyer GREEN and buyer RED are automats that flips a fair coin in order to determine which seller to purchase from.	
	7. Each seller have three units to offer.	
	8. Finally profit is distributed and the period ends.	
	* The profit of a seller equals the price times the number of units sold.	
	* The profit of a buyer that buys a unit equals 100.00 schilling minus the price paid.	
		ОК

Period	
2 outof 50	Remaining time [sec; 0
You are: selle	r CIRCLE
Please enter a binding price between 0.00 and 100.00	schilling that you are willing to sell your unit for:
	10
REMEMBER, the market has:	
*Two sellers: seller CIRCLE and seller SQUARE	
*One informed buyer: buyer BLUE	
*Two uninformed buyers: buyer GREEN and buyer RED (the automats)	
	ок

Period		
	2 out of 50	Remaining time [sed]: 4
	Vou are:	collor SOUADE
	100 816.	
	The seller second	
	THE SERVICE OFFICE	en at prices (schnnig).
		10.00
	SOLIARE	12.00
	340Anc	12.00
		OK

Period 2 out of 50	Remaining time [sec]: 0
You are:	buyer BLUE
Sellers offers to sell	at prices (schilling):
CIRCLE SQUARE	10.00 12.00
Choose a sei	ier to buy from
0 0	CIRCLE SQUARE
REMEMBER, the market has:	
*Two sellers: seller CIRCLE and seller SQUARE *One informed buver, buver BLUE	
*Two uninformed buyers: buyer GREEN and buyer RED (the automats)	

- Period -	
2 out of 50	Remaining time [sec]: 4
You are buyer BLUE	
Queue of buvers at	
seller CIRCLE 1	
Sener Suuare 2	
	ОК

- Period	2 out of 50							Remaining time [sec]: 19
				You are seller C	SIRCLE			
			Your a	accumulated profit 10.	00			
								ОК
Period	Price CIRCLE	Price SQUARE	Queue CIRCLE	Queue SQUARE	Choice BLUE	Choice RED	Choice GREEN	Your profit
2	10.00	12.00	1	2	Seller CIRCLE	Seller SQUARE	Seller SQUARE	10.00