Information and coordination frictions in experimental posted o er 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 di erent 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. The latter result, rst shown by Lester (2011), is counter-intuitive and we thus call it Lester's paradox. In the experiment, the di erences between the constrained and non-constrained case are con rmed; prices fall when sellers are not capacity constrained but either do not fall by much or even increase when they are not. Hence we nd support for Lester's paradox. We nd that prices are quite close to the predicted equilibrium values except in treatments were unconstrained sellers face a large fraction of informed buyers. Here deviations can be substantial. However, introducing noise into the theoretical decision making process produces a pattern of deviations that ts well with the observed ones.

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1 Introduction

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

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

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

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

In a recent paper, Lester (2011) introduces information frictions into a market setting with capacity constraints. He demonstrates that increasing the fraction of informed buyers may pned sell up to three units or have only one unit in stock (the capacity constrained case).

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

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

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

In our treatments with capacity constraints we test for equilibria in which buyer-coordination is not permitted. The study by Ochs (1990) analyzes how the degree of coordination depends on are not capacity constrained, $z = c$ indicates that they are.

The expected payoff of a sellers is $^{z}_{s}(p_s; p_{\ s}) = \ ^{z}(p_s; p_{\ s})p_s$, where $^{z}(p_s; p_{\ s})$ is the expected number of sales given by the number of units in stock (z), the own price and the prices of other sellers. The expected payoff of a buyer i conditional on choosing a seller s is $v^z_i(\ ^s_{\ i}) = \ ^z(\ ^s_{\ i})(1 \ p_s)$, where $^z(\ ^s_{\ i})$ is the probability of getting the good at seller s given that the other buyers go to this seller with probabilities $^s_{\ i}$. 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 $^s_i = 1{=}S$ for all $i \ 2 \ U$. We focus on sub-game perfect equilibria with symmetric (mixed) strategies. While this is the standard assumption in the theoretical literature, it is also justified in our experimental set-up since market participants are anonymous and new markets are formed randomly in each period, making coordination difficult.

Equilibria with no Capacity Constraints We first look at the case where there are at least some uninformed buyers, $U \ 1$: 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 $^n(p_s; p_{\ s}) = N + U{=}S$ if p_s is the lowest price and $^n(p_s; p_{\ s}) = U{=}S$ otherwise.[7] One can show that the symmetric equiby $1 \quad (1 \quad F(p))^{S}$. By using the tail formula again it follows that the expected minimum price at which the informed buyers purchase the good is given by:

$$E[p_{min}] = p_0 + {}_{p_0}^{1} \; \frac{1 \quad p}{}$$

As is common in directed search models, we focus on symmetric mixed buyer strategies. In equilibrium informed buyers have to be indi erent 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 $v_i^c(\ ^{s^0}_i) = v_i^c(\ ^{s^{00}}_i)$ for any $s^0, s^{00} 2$ S such that $^s_i >$ 0, s = s^0, s^{00}. Together with the requirement $P_s \ ^s = 1$ this gives a system of equations that implicitly determines the functions f $^s(p_s; p \ _s)g_{s2S}$; which sellers use in the rst stage to forecast buyer behavior.

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

$$^c(p_s; p \ _s) = 1 \quad (1 \quad ^s(p_s; p \ _s))^N (1 \quad 1{=}S)^U :$$

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 pro t maximization problem

$$\max_{p_s} \ ^c(p_s; p \ _s)p_s$$

given that all the other rms charge the equilibrium price p . The seller forecasts the buying probability $^s(p_s; p \ )$ from the indi erence condition of the buyers: $^c(\ ^s)(1 \quad p_s) = \ ^c((1 \quad ^s){=}(S \quad 1))(1 \quad p \ )$. Substituting the conditions of a symmetric equilibrium, i.e. $p_s = p$ and $^s(p \ ; p \ ) = 1{=}S$; into the rst order condition of the rm's problem, one can solve out the (unique) equilibrium price:

$$p \ = M{=}[M + (1 \quad (p \ ; p \ )) \ (1{=}S) f N (B \quad 1){=}(S(N \quad 1))$$

3 Parameters and Procedures

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

In all treatments prices and payoffs were measured in experimental currency units (ECUs).

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

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) at fee of 27 US dollars plus whatever they earned in the session. This was done in order to avoid sellers not earning money in the experiment. In all other treatments subjects got what they earned plus a show up fee. Earnings in the Konstanz treatments were adjusted to give the same consumer purchasing power as the Oslo treatments.

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

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

z	N: 1	2	3
n	$E(p) = 69{:}3$ $p \in [50; 100]$ $F(p) = \frac{2p - 100}{p}$ $E(p_T) = 66{:}$	$E(p) = 40{:}2$ $p \in [20; 100]$ $F(p) = \frac{5p - 100}{4p}$	$E(p) = 0{:}0$

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

4 Results

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

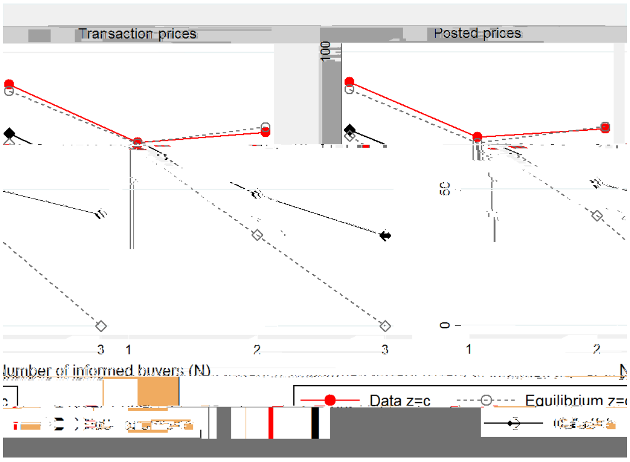

Figure 1: Posted prices and transaction prices for each treatment. Average posted prices (transaction prices) for treatments T_1^n to T_3^c are 71.4 (68.8), 52.3 (44.3), 41.6 (32.2), 89.1 (88.0), 68.9 (66.5), 71.9 (70.3), respectively.

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

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

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

For posted prices the di erences 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 signi cant at the 1% level.

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

Furthermore, posted prices decrease when going from treatment T_1^n to T_2^n (W=2.611; p=.005); and when going from T_2^n to T_3^n (W=2.193; p=.014). These price decreases are signi cant at the 5% level or better. WRS tests also reveal that posted prices decrease signi cantly from treatment T_1^c to T_2^c (W=2.611; p=0.005). The increase in posted prices from treatment T_2^c to T_3^c, however, is not signi cant at conventional levels (W=-1.149; p=0.125). Nonetheless it is close to being signi cant at the 10% level, and we nd 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 ve observations in each treatment.

Result 2 (Treatment di erences for posted prices) *The di erences in posted prices between the treatments with and without capacity constraints for a given number of informed buyers are all signi cant. 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 signi cant.*

Our results become stronger for transaction prices. The di erences 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 signi cant 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 signi cant at the 1% level or better. WRS tests also show that transaction prices decrease signi cantly 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 signi cant at the 10% level, and almost signi cant at the 5% level (W=-1.567; p=.059). [13]

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

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

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

Table 3: Treatment regressions.

	PP I	PP II	TP I	TP II
Constant	40.9	37.4	33.6	29.2
	(2.93)	(2.24)	(2.42)	(1.78)
T_1^n	28.6	30.4	34.7	37.2
	(3.97)	(2.94)	(3.62)	(2.67)
T_2^n	9.5	11.3	12.7	15.1
	(3.95)	(3.18)	(3.42)	(2.93)
T_1^c	42.7	48.1	48.7	55.0
	(3.52)	(2.51)	(3.14)	(2.19)
T_2^c	24.8	28.0	30.1	

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

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

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

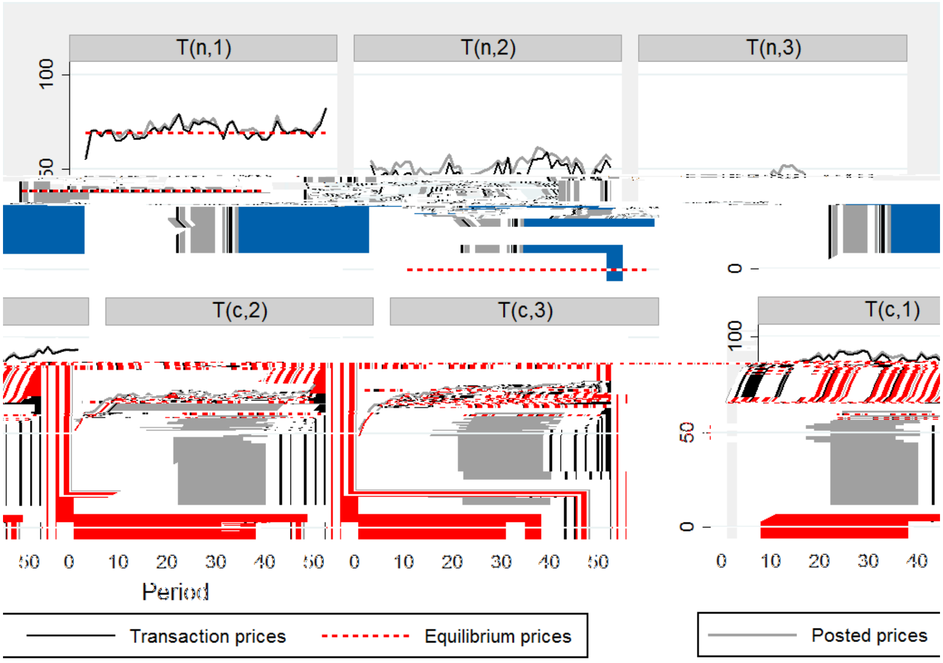

Figure 2: Average posted prices and average transaction prices over periods.

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

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

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

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

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

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

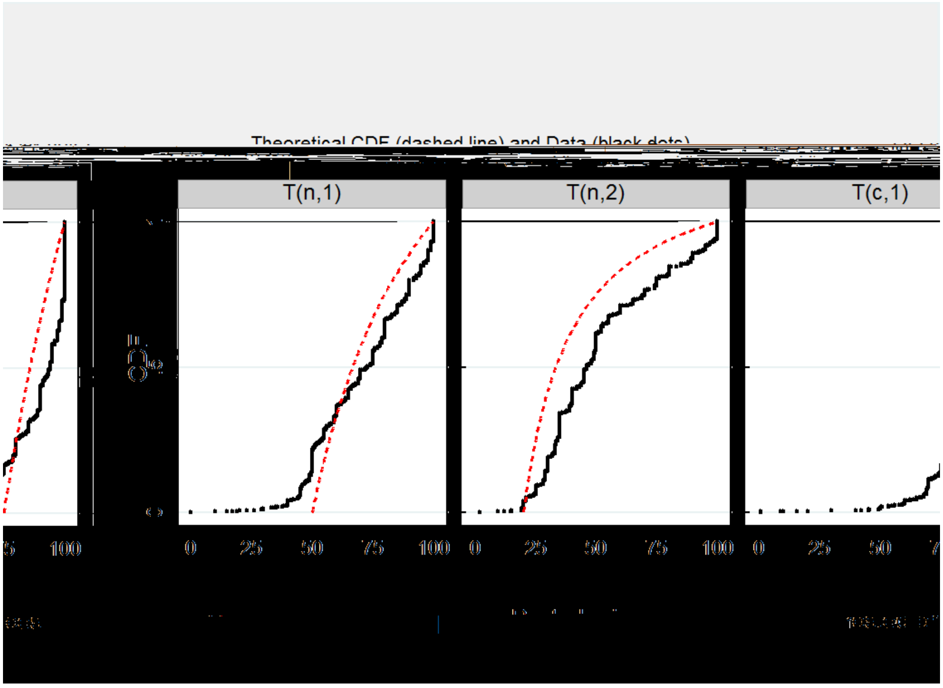

Figure 3: Cumulative price distributions T_1^n, T_2^n, and T_1^c: Data and theoretical prediction

To evaluate the optimality of buyer responses in these treatments we used the following procedure

Surprisingly, informed buyer responses seem, if anything, to correspond better with theory when

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

Table 6: QRE estimates

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

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

Figure 5 shows the tted distributions and the data.

Figure 5: QRE distributions and actual posted price distributions.

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

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

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

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

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

To be concrete, let the expected pro ts of a seller be a function of her own price and a partly behavioral strategy of the other seller. By "partly behavioral" we mean that the price distribution the other seller uses is a convex combination of the equilibrium price distribution from theory and a behavioral price distribution. We consider three examples, a mixture of the equilibrium distribution with a price distribution that is positively skewed (F (

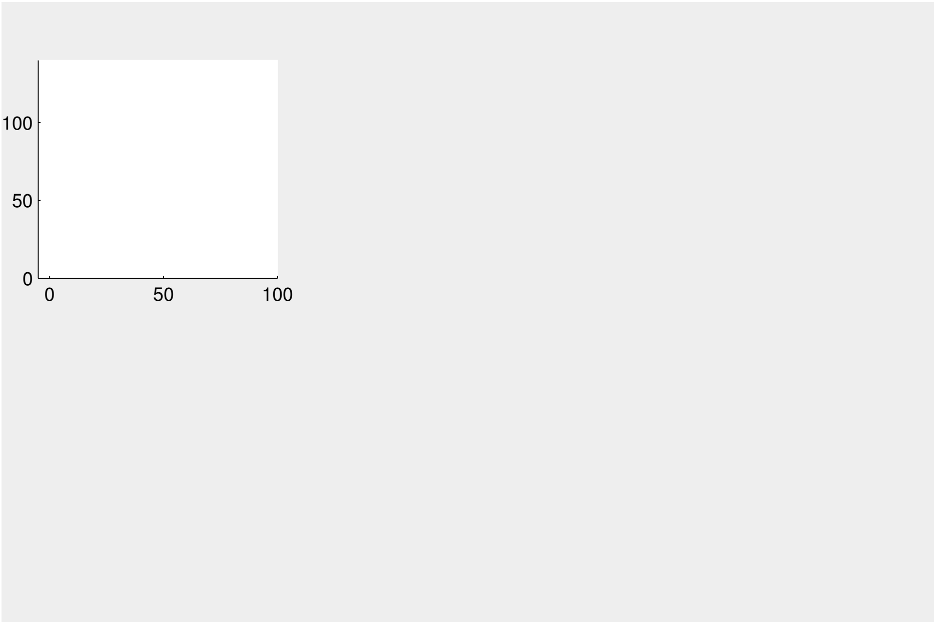

Figure 6: Expected profits as function of the own price given a 75-25 mixture between the equilibrium distribution and a "noisy" distribution of the other player. Vertical dashed lines indicate theoretical expected prices and solid lines average prices in the data.

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

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

Comparison to previous experiments. How do our results compare to existing ones? Cason and Noussair (2007) (hereafter CN) test the Burdett, Shi, and Wright (2001) model. Our design is very close to theirs. CN find average posted prices of 83.7 for periods 39-48.[21] In comparison, average posted prices in periods 39-48 is 72.5 in our T_3^c treatment. So, while CN overshoot the equilibrium value by 11 percentage points in these 10 periods, we overshoot by only 2.2 percentage points. Finally, our data converge more rapidly on a value closer to equilibrium in the T_3^c treatment than the CN data does.[22]

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

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

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

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

posted prices over all periods, AF undershoot the equilibrium value by 13.5 percentage points.[24] Averaging posted prices only over the last 5 periods reduces this undershooting to 9.7 percentage points.

In general, buyer reactions in our58r

Summing up, we succeed in replicating the behavioral patterns of existing experiments for treatments T_1^n,

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6 Appendix

6.1 Some Calculations for the Theoretical [redacted]ictions

Here are the predictions for the cases of $S = 2$ a[redacted] $= 3$, with $N > 0$. For the case without capacity constraints with $N < 3$ we can easily in[redacted]e (2) to get:

$$E[p] = \frac{3}{2N} \text{[redacted]} \frac{3 - N}{3 + N} :$$

Similarly, for the expected minimum price we obt[redacted]

$$E[p_{min}] = \frac{3 - N}{N} + \text{[redacted]} N)^2$$

E[N ln 3 N6 [(11924 Td [(S

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 $2\ (\frac{1}{4}\ 1 + \frac{1}{4}\ 1 + \frac{1}{4}\ 2 + \frac{1}{4}\ 0)\ 1 = 2$. The expected number of sales is 3 as all buyers will obtain a good. Thus average profit and price equals $E[p_T] = 2/3 \quad .667$.

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

Treatment T_1^c: The probability of meeting the uninformed is given by $1 \quad (1 \quad 1/S)^U = 3/4$ 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 $E[p_T] = \frac{2\ 3/4\ 1}{7/4} = 6/7 \quad .857$.

6.2 Buyer responses z=c case

Here we compute the individual buyer's best response functions $^1(p_1;p_2)$ from the indifference condition $^c(\ ^1)(1 \quad p_1) = \ ^c(1 \quad ^1)(1 \quad p_2)$ for cases $N = 2$ and $N = 3$:

$N = 2$ case:

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

$N = 3$ case:

$$^1(p_1;p_2) = \begin{cases} 0.5 & \text{if } p_1 = p_2 \\ 0 & \text{if } 2 + p_2 \quad 3p_1 \quad 0 \\ 1 & \text{if } 2 + p_1 \quad 3p_2 \quad 0 \\ (4 \quad 3p_1 \quad p_2 \quad p\ \overline{16(1 \quad p_1 \quad p} & 1\ E\ 9 \end{cases}$$

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

Table 7: Convergence regressions

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

Dependent: posted prices. Prais-Winsten regressions treatment by treatment, with seller random e ects. Coe cients (standard errors).

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

Next, consider Table 8. Except for treatments T_2^n to T_3^n, the estimate of $_2$ is less than ve 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 di erence between $_2$ and the equilibrium can be rejected. In treatment T_3^c this null cannot be rejected.

The variance of posted prices generally declines over time in each treatment. Except for T_2^n variance declines in a majority of the matching blocks, and in T_1^n, T_1^c and T_3^c variance declines inn all ve matching blocks, as shown in table 9. Qualitatively, the regressions are consistent

Table 8: Equilibrium convergence

Tr	11	12	13	14	15	2	$E(p)$	H_0^B
T_1^n	56.2	57.6	42.4	73.8	50.6	72.7	69.2	.000
	(6.55)	(9.50)	(9.62)	(8.97)	(8.79)	(0.91)		
T_2^n	56.2	53.3	51.1	63.1	46.2	52.0	40.2	.000
	(9.04)	(7.82)	(8.22)	(10.28)	(6.03)	(1.00)		
T_3^n	52.7	34.1	59.1	41.9	48.3	40.0	0.0	.000
	(9.43)	(9.87)	(6.61)	(10.03)	(8.44)	(1.08)		
T_1^c	63.7	59.5	78.4	53.1	77.9	91.2	86.3	.000
	(4.66)	(5.58)	(4.94)	(5.05)	(3.55)	(0.69)		
T_2^c	61.7	59.8	54.3	56.2	59.5	69.8	66.7	.000
	(4.10)	(3.43)	(6.63)	(4.71)	(3.88)	(0.70)		
T_3^c	47.1	51.3	57.7	54.7	58.7	73.6	72.7	.173
	(5.85)	(4.78)	(2.25)	(3.11)	(3.45)	(0.67)		

Dependent: posted prices. Prais-Winsten regressions treatment by treatment, with seller random e ects . Coe cients (standard errors).

Table 9: Variance in posted prices

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

Dependent: Variance in posted prices. Prais-Winsten regressions treatment by treatment, with seller random e ects. Coe cients (standard errors).