Possible Collusion and Equilibrium Prices[*]

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Abstract

We investigate how possible collusion, interpreted as a positive prior probability that collusion may occur, influences equilibrium prices in states of the world in which collusion, in fact, does not occur. We explore the mechanism in a theoretical model of consumer search, based on the Stahl (1989) framework, and show that with possible collusion, equilibrium prices are higher even in the absence of collusion. We test the model predictions in a series of laboratory experiments. The results are qualitatively consistent with our theoretical predictions.

Keywords: Consumer search, collusion, asymmetric information, market experiment

JEL: D82, D83, L13, C92

[*] The research is financed by the Norwegian Business School BI. We would like to thank Joe Harrington for comments on an earlier draft, and participants at the BECCLE annual conference on competition policy, at the CESAR 2024 workshop on experimental economics, and at Department seminar at the Norwegian Business School BI.

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1 Introduction

Collusion, almost by definition, leads to higher prices. The focus in this paper is on how possible collusion, interpreted as a positive prior probability that collusion occurs, may influence equilibrium prices in states of the world in which collusion, in fact, does not occur. Fear of collusion may influence the search behaviour of consumers. In particular, possible collusion may reduce consumers' incentives to continue searching after being offered a high price. Non-colluding sellers may take advantage of this and set higher prices than when there is no potential for collusion.

We first explore this mechanism in a theoretical model of consumer search based on the Stahl (1989) framework. The model contains two features that are crucial for our mechanism to work. First, buyers believe that collusion may take place with strictly positive probability. Second, buyers are not fully informed about the prices offered by all sellers and may search to obtain more price quotes.

In the simplest version of our model, there is an exogenous probability that the sellers may collude on a price p^M. This price is higher than any price offered in equilibrium in the absence of potential collusion and would not have been accepted by any consumer. In the presence of potential collusion, the situation is different. When a consumer visits a seller that posts p^M, she updates the probability that firms collude and buys the good with a strictly positive probability. This in turn induces some sellers to set p^M even in the absence of collusion, and the entire price distribution shifts upward. As a result, equilibrium prices are higher even when collusion, in fact, does not occur.

In the second part of this paper, we explore the mechanism in a laboratory experiment. In our experiment, participants have roles as sellers or buyers. The probability that sellers collude varies between the treatments. When collusion occurs, prices are set exogenously at p^M for all sellers. We run a total of four treatments. In our control treatment, the exogenous probability of collusion is zero. In the three remaining treatments, the exogenous probability of collusion is 10% , 20% and 30%, respectively. The equilibrium outcome according to our model is the same in these three treatments.

The results from the experiment fit the model predictions surprisingly well. Without collusion, the results are more or less spot on compared with theory. When we look at the average effect of fear of collusion over the three treatments with a positive probability of collusion, we find that potential collusion leads to a mass point in the price distribution at the collusive price p^M and an upward shift in the remaining price distribution below p^M. Both of these findings are in line with theory. The average posted prices in the experiment increased by 14.9, 54%, from 27.62 to 42.47 units (see Table 2). The predicted price increases with 18.2 units, 75%, from 24.4 to 42.6 units (see Table 1). However, the averages hide differences between treatments with collusion which inconsistent with the theory, and prices are higher than expected in the $T30$ treatment and lower than expected at the $T10$ treatment (with 30 and 10 percent probability of collusion, respectively). Regarding search behaviour, we find that search rates are low across all treatments, which is in accordance with our theoretical predictions.

Although there are deviations from equilibrium predictions in the data, both buyers and sellers best-respond remarkably well. Across our four treatments, the share of buyer decisions that are consistent with a best response, given the empirical reservation price, ranges between 91 and 97 percent. Furthermore, we find that most of the posted prices are within the ranges that yield the highest profits. Thus, the pricing behaviour of sellers is to a large extent profit maximizing.

Hence, our hypothesis that fear of collusion may influence prices even in the absence of actual collusion has support, both from our model and from our experiment. An important question then is for which markets our theory may be relevant. Criteria

The first two criteria are satisfied for most retail markets. Some retail markets, such as the gasoline market, have a reputation for being riddled with anti-competitive

Related Literature

Our paper contributes both to theoretical and experimental literatures related to markets with search and to markets with collusion.

First, we contribute to the theoretical literature on consumer search with learning. In this literature, consumers do not know the costs of the di erent sellers, but they know that they are correlated (see. e.g., Benabou and Gertner (1993) and Dana Jr (1994) for early contributions).[3] The paper closest to ours is Janssen et al. (2011), who include cost uncertainty in the Stahl (1989) model with consumer search. They do so by assuming that sellers have stochastic, but perfectly correlated costs unobserved by the consumers, and show that this cost uncertainty raises prices for both informed and uninformed consumers. The same model with equilibrium re nements is analyzed in Janssen et al. (2017). Our model is similar to these models in that consumers are uncertain about the distribution of prices in the market. However, the sources of uncertainty are di erent, in our model prices are uncertain because of possible collusion, not because of uncertain costs. In addition to being conceptually di erent, this makes our model much more tractable, and eliminates the need for equilibrium re nements.

There is also a string of related papers on consumer search that includes consumers' inferences about downstream rms' costs in vertical market contexts (see, e.g., Janssen and Shelegia (2015), Lubensky (2017), Janssen (2020) and Janssen and Shelegia (2020)).[4]

Second, our paper relates to the literature on consumer search and collusion in repeated games, see e.g., Nilsson et al. (1999), Campbell et al. (2005), Petrikait e

[3]There are also papers that extend this model framework to a dynamic setting, and analyze how autocorrelation in costs a ects pricing dynamics (see e.g., Yang and Ye (2008) and Tappata (2009)).

[4]There also several papers with consumer search where consumers learn about other states of the market than production costs. In Lauermann et al. (2012) traders gradually learn about market demand and supply through a sequence of multilateral bargaining rounds. Atayev (2022) studies uncertainty about product availability. Mauring (2017) and Mauring (2020) analyze how consumers learn about the price o er distribution from past searchers' trading decisions in an environment with non-strategic sellers.

(2016), Montag and Winter (2020), and Shadarevian (2022) for theoretical contributions.[5] The only experimental studies of collusion in search markets are Moellers et al. (2016) and Orzen (2008), who study repeated game versions of the Stahl (1989) model and the Varian (1980) model, respectively.[6] A common characteristic of these studies of repeated games is that buyers know the state of the game, i.e., whether rms are on the equilibrium path or on the punishment path. In contrast, in our pa-

The remainder of the paper is organized as follows. Section 2 outlines the theoretical framework, and Section 3 presents our experimental design and procedures. In Section 4 we report the results from our experiment, while Section 5 offers a brief conclusion.

2 Mechanism and Model

Before we dive into the model, we will discuss the underlying economic mechanism, which we believe applies more broadly than in our model environment, as long as prices are influenced by consumer search.

2.1 Mechanism

Our mechanism is related to the beliefs and incentives of searching consumers. A core element is that a subset of consumers have limited information about the prices set by the different sellers and that they can gather information about prices through costly search. If a consumer visits a seller and finds that the price is high, the consumer will continue searching and visit another store if the expected gain from doing so is higher than the search cost. The consumers' search behaviour disciplines the sellers when setting prices and leads to lower equilibrium prices.

The risk of collusion corrupts this mechanism, as collusion induces price quotes from different sellers to be correlated. Suppose first that consumers know that there is a probability that the sellers collude and set higher prices. A buyer who visits a store that charges a high price will not know if this high price reflects a high-price strategy of the seller, i.e., a seller-specific high price, or if it is due to collusion. If it is a seller-specific high-price strategy, the consumer may want to search again. However, if it reflects collusion, the gain from search is lower or non-existence, as the other sellers will charge a high price as well. Therefore, an *a priori* positive probability of collusion will reduce the incentives of buyers to continue searching after observing a high price.

This induced change in consumer search will, in turn, influence seller behaviour. If the sellers know that buyers search less due to the fear of collusion, they may be tempted to set a high price even in the absence of collusion, as the probability of being rejected by the consumers is lower. They may use the possibility of collusion as a "disguise" for a seller-specific high price. Hence, the possibility of collusion will induce some sellers to set a high price without collusion.

Since prices are strategic complements, this will give rise to "multiplyer effects", and in principle induce all sellers to set higher prices. Let us be more specific at this point. A common feature of price models with search frictions is that they generate price dispersion, and this gives rise to a source of amplification. As some sellers set a higher price to mimic price collusion, the competition among sellers setting lower prices softens. Hence, the entire price distribution shifts up, leading to even higher average prices.

In the rest of this section, we will explore these mechanisms in the Stahl (1989) model, a work-horse model within consumer search.

2.2 Model set-up

We consider the Stahl model, with consumers' willingness to pay equal to 1, and with parameters such that the supremum of the price support in the Stahl equilibrium, denoted p_S, is strictly below 1. With exogenous probability x firms collude on a price $p^M > p_S$. Let c denote the search costs for consumers of searching to obtain a second price quote. Let u denote the number (measure) of uninformed customers per seller and I the number (measure) of informed customers. The number of sellers is 2. The costs to the sellers are normalized to zero. We will derive the equilibrium of the model an interval $[p_0; p_1]$, where $p_1 < p^M$. From standard arguments it follows that $F(p)$ is continuously distributed with no holes, see Varian (1980). Consumers observing prices in the interval $[p_0; p_1]$ do not search, and consumers at p_1 are indifferent between searching and not searching. No seller sets a price in the interval $(p_1; p^M)$. If it does so, the consumers will understand that there is no collusion, and therefore search, and the seller is worse off than if setting p^M.

Hence the possibility of collusion induces some firms to set p^M, which is the direct effect of collusion. As a result, to be shown below, the entire distribution F shifts up, and this reflects what we above referred to as the multiplier effect.

We will distinguish between two equilibrium candidates, one without consumer search and one with consumer search. In the equilibrium candidate without consumer search, uninformed consumers do not search after observing the monopoly price p^M. In the equilibrium candidate with consumer search, uninformed consumers search after observing p^M with an endogenous probability $q \in (0; 1]$. As will be clear below, which of the equilibrium candidates constitutes an equilibrium depends on the prior probability x of collusion: the equilibrium without search exists if x is above a certain threshold, while the equilibrium with search exists if x is below the same threshold.

2.3 Equilibrium without consumer search

Suppose first that consumers do not search if they observe $p = p^M$. Then the profit of a firm that sets a price at or below p_1 is

$$\pi = p[u + \lambda I + (1 - \lambda) I (1 - F(p))] = p\left[\tilde{u} + \tilde{I}(1 - F(p))\right] \quad (1)$$

where $\tilde{u} = u + \lambda I$ and $\tilde{I} = (1 - \lambda) I$. Hence, for a given p_1, the equilibrium distribution $F(p)$ is identical to the Stahl equilibrium distribution with $u^0 = \tilde{u}$ uninformed consumers per seller and $I^0 = \tilde{I}$ informed consumers. Equation (1) states that the profit of a firm that sets a price p in the interval $[p_0; p_1]$ is equal to the price times quantity sold. The seller sells to u uninformed consumers, and to all the informed consumers if the opponent sets a price either equal to p^M (which happens with probability) or in the interval $[p_0; p_1]$ but above p (which happens with probability $(1 \quad)(1 \quad F(p))$).

The gain from search at p_1 is given by $(1 \quad) \int_{p_0}^{p_1} F(p)dp$. The rst factor re ects that the other seller can set a price of p^M, in which case the gain from search is zero. The second factor is the gain from search conditional on the other seller not setting p^M.

The equilibrium candidate without consumer search is a value $\quad 2 [0; 1]$ and a distribution $F(p)$ with support $[p_0; p_1]$ satisfying the following conditions:

1. Equal pro t when setting p^M and p_1:

$$p^M (u + \frac{I}{2}) = p_1(u + \quad I \quad) \qquad (2)$$

2. Equal pro ts for all $p \, 2 \, [p_0; p_1]$, implying that $F(p)$ given by

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p^M will be strictly better o undercutting p^M slightly and attract all the informed customers if the opponent sets p^M (which happens with strictly positive probability).

Third, if $p^M > p_s$, then $p^M > p_1$ in equilibrium. Suppose not, i.e., suppose $p^M \quad p_1$. Suppose > 0. Then the undercutting argument from Varian (1980) again applies, and we cannot be in equilibrium. Suppose $= 0$. Then consumers will always know whether collusion takes place or not, and we must have $p_1 = p_s < p^M$, a contradiction.

Result 1. Suppose $p_s < p^M$. Then the equilibrium candidate without consumer search exists and is unique.

Proof. For any given , the continuous part of the model, equation (3) and (4), is isomorphic to the Stahl model with $u^0 = u$, $I^0 = I$, and $c^0 = c=(1 \quad)$, and it follows easily that F and $[p_0; p_1]$ exist and are unique. Let $p_1( )$ denote the corresponding value of p_1. It follows that $p_1( )$ is continuous in .

De ne $^1( )$ as the pro t at $p_1( )$ and $^M( )$ the pro t at the collusion price. Both are continuous in . Hence, to show existence, it is su cient to show that $(0) < {}^M(0)$ and that $_1( ) > {}^M( )$ for some > 0.

For $= 0$, sales at p^M are the same as at p_1, hence $^M(0) > {}_1(0)$. For high values of , $p_1 = 1$. Hence, there exists a lowest value $2 (0; 1)$ such that $p_1( ) = p^M$. For p_1 su ciently close to p^M, $_1( ) > {}^M( )$, since the sales at p_1 are $I = 2$ higher than at p^M. It follows that for su ciently close to , $_1( ) > {}^M( )$. Hence, there must exist a value of $<$, which we denote such that $_1( ) = {}^M( )$. This completes the proof of existence.

Uniqueness requires that equation $_1( ) = {}^M( )$ has a unique solution. It is su cient to show that, evaluated at , $_1( ) \quad {}^M( )$ is increasing in (then the curves cannot cross twice).

First note that at , $^M = {}_1$, and hence

$$(p_1 \quad p^M=2) I = u(p^M \quad p_1) > 0;$$

hence $p_1 > p^M=2$. Now

$$\frac{d}{d}(\;_1 \quad ^M) = (p_1 \quad p^M=2)l + \frac{dp_1}{d}(l + u) > 0$$

evaluated at , since $p_1 > p^M=2$ and $\frac{dp_1}{d} > 0$.

□

It should be noted that the equilibrium price distribution is independent of x, the probability that collusion takes place. When rms set prices, they know that collusion does not occur. When consumers observe a price di erent from p^M, they also know that collusion does not occur. Only if consumers observe p^M, they are uncertain whether collusion has taken place or not. In this section x is assumed to be so high that consumers do not search when observing p^M, and hence their beliefs do not in uence equilibrium. In the next subsection, we relax this assumption.

2.4 Conditions for consumer search

A consumer who observes p_1 is indi erent between searching and not. A consumer who observes p^M does not know if there is collusion or not, and this reduces the incentives to search.

Given that a consumer observes a price p^M, the conditional probability that collusion takes place is given by $x^M = \frac{x}{x+(1 \quad x)}$ (by Bayes law), and the complementary probability (that collusion does not take place) is $1 \quad x^M = \frac{(1 \quad x)}{x+(1 \quad x)}$.

If there is collusion, the gains from search is zero. Suppose that there is no collusion. We compare the gains from search at p_1 and p^M. If the other rm sets p^M, the gains from search is zero both at p_1 and p^M. Otherwise, the gains from search is $p^M \quad p^1$ higher at p^M than at p_1. The expected gains from search are equal to at p_1, since the consumer at p_1 is indi erent between searching and not. Hence, for there to be no search at p^M, we must have that

$$(1 \quad x^{M})\ \ c + (1 \quad)(p^{M} \quad p_{1}) \quad c \qquad (5)$$

or that

$$\frac{(1 \quad x)}{x + (1 \quad x)} \qquad \frac{c}{c + (1 \quad)(p^{M} \quad p_{1})} \qquad (6)$$

The left-hand side, the probability that there is no collusion given that the consumer observes p^{M}, is strictly decreasing in x for a given

2.5 Equilibrium with consumer search

Suppose then that (6) is not satisfied and that consumers observing p^M choose to search with probability q. We then have one new equation that must be satisfied, (6) with equality, and one more variable to be determined, q. Furthermore, q will influence the profitability of setting a low price, and hence the other equilibrium equations. Specifically, there will be more uniformed consumers searching. However, the structure of the equilibrium is the same as before. The price distribution has a mass point at p^M. Conditional on not setting p^M, the sellers set prices according to a continuous distribution function $F(p)$ with support $[p_0; p_1]$.

Consider a seller who sets a price $p \in [p_0; p_1]$. She will get u uninformed buyers directly. In addition, there is a probability α that the other seller sets p^M, attracting u uninformed buyers, and q of these ($q\alpha u$ in expectation) will search again and end up at our seller. Finally, she will get all informed customers if and only if the other seller sets a price above p. Hence, the profit of this seller is

$$\pi(p) = p[(1 + q\alpha)u + \alpha I + (1 - \alpha)I(1 - F(p))] = p(\tilde{u} + \tilde{I}) \quad (7)$$

with $\tilde{u} = (1 + q\alpha)u + \alpha I$, and with $\tilde{I} = (1 - \alpha)I$ (as before), analogous with (1).

The equilibrium candidate with consumer search is defined as two values $\alpha \in [0; 1]$ and $q \in (0; 1]$, and a continuous distribution function $F(p)$ on $[p_0; p_1]$, satisfying

1. Equal profit when setting p^M and p_1:

$$p^M(u(1 - q) + I = 2) = p_1(u(1 + q\alpha) + \alpha I) \quad (8)$$

2. Equal profits for all $p \in [p_0; p_1]$, or from (7):

3. Consumers at p_1 are indifferent between searching and not searching :

$$(1 \quad) \int_{p_0}^{p_1} F(p)dp = c \tag{10}$$

If the solution to (10) is greater than 1, then $p_1 = 1$

4. Consumers at p^M are indifferent between searching and not searching:

$$\frac{(1 \quad x)}{x + (1 \quad x)} = \frac{c}{c + (1 \quad)(p^M \quad p_1)} \tag{11}$$

A remark on the nature of the equilibrium is here in place. The game is sequential, in that sellers first set prices and then buyers respond, and both buyers and sellers play with mixed strategies at p^M. When visiting a seller that sets p^M, the strategy of the other seller makes the buyer indifferent between searching or not. One may wonder why a seller does not slightly undercut p^M to ensure that buyers buys with certainty. The point is that this strategy does not work, as the consumer then learns that there is no collusion and will search with probability 1.

Result 3. Suppose $x < x$. Then the equilibrium candidate with consumer search exists and constitutes an equilibrium of the game.

Proof. For any given and q, at the interval $[p_0; p_1]$, the equilibrium is isomorphic to the Stahl model with $u^0 = u$, $l^0 = l$, and $c^0 = c=(1 \quad)$ (see equations 9 and 10), and it easily follows that F and $[p_0; p_1]$ exist, are are unique, and are continuous in and q (p_1 is bounded above by 1, but as will be clear below that will not be binding).

We show existence as follows. We construct a mapping $: [0; 1] \quad [0; 1] \mapsto [0; 1] \quad [0; 1]$ as follows:

For a given pair $(; q)$ in the domain, calculate $p_1(; q)$. If $p_1(; q) > p^M$, define $p_1(; q) \quad p^M$. Given p_1, calculate $_1(p_1)$ and ^{M} (suppressing the dependence of and q), where $_1(p^M) \quad \lim_{p_1 \to p^M} \ _1(p_1)$. Define

$$k_1 = \frac{\quad^{M} \qquad {}_1(p_1)}{\max f \;\; {}_M \, ; \;\; {}_1(p_1) g}$$

Then update as follows:

$$\quad^0 \qquad (\; ; q) = \quad (1 + \min[\, k_1; 0]) + (1 \qquad) \max[k_1; 0] \qquad (12)$$

By construction, $\;^0 2 \; [0; 1]$

Then consider the update of q. De ne k_2 as (from 5)

$$k_2 = \frac{(1 \quad x^M) \quad c + (1 \qquad)(p^M \qquad p_1) \qquad c}{\max f \, (1 \quad x^M)\,(c + (1 \qquad)(p^M \qquad p_1)) \; ; c g}$$

Then update q according to

$$q^0 \qquad {}_q(\; ; q) = \; q\,(1 + \min[\, k_2 \ldots \qquad q) \max[k_2 \ldots]$$

The mapping $(\; ; q) = (\quad (\; ; q); \; {}_q(\; ; q))$ is by construction continuous and bounded on $[0; 1]$ $[0; 1]$. From Brouwers xed point theorem it follows that the mapping has a xed point. This xed point will satisfy all equilibrium criteria, provided that $p_1 < p^M$. Hence, we only have to show that $p_1 < p^M$. But this follows directly from the fact that (8) cannot be satis ed for

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we have shown (numerically) that the equilibrium is unique.

As already mentioned, the equilibrium without search is independent of x provided that x x. It follows easily that in the no-search equilibrium increases in p^M. This follows from the fact that the left-hand side of (2) is increasing in p^M while the right-hand side is independent of p^M for a given .

The next question is what happens if x ! 0. We can show that in this case ! 0. Otherwise, it follows from (11) that the the left-hand side of the equation, the probability that there is no collusion, goes to 1, while the right-hand side is strictly less than one. Hence all consumers search at p^M and we cannot be in equilibrium.

2.6 Extensions

In the appendix, we study two extensions of the model. First we extend the model to allow for n sellers. The structure of the equilibrium is unchanged, but the expression for F becomes more involved. Second, we assume that the prices in case of collusion are drawn from a continuous distribution $G(p)$ on an interval $I^M = [p^{min}; p^{max}]$, known to consumers. We show that in the absence of collusion, sellers post prices on $[p^{min}; p^{max}]$ according to a continuous distribution function without mass points. Furthermore, if $p_1 < p^{min}$, consumers search (with some probability) at the lower part of I^M but not necessarily at the higher part. The analysis of these two extensions are not yet complete.

3 Experimental design and procedures

The aim of the experiment is to empirically investigate the fundamental mechanism of our model. To accomplish this objective, we will compare pricing and searching decisions in two di erent scenarios: one where pricing is always determined endogenously, and another where prices may be set exogenously at the collusive level.

We have four main treatments. In our baseline treatment, T0, the price is never

is automated.[11] If a buyer pays to observe the price of the other seller, the buyer purchases from the other seller if and only if that seller has a lower price.

Figure 1: Theoretical price distributions by treatment

Table 1: Theoretical predictions

	$T0$	$T10$, $T20$ and $T30$
$E(p)$	24.4	42.6
p_0	14.8	26.5
p_1	44.4	62.6
	0	0.13

Based on the theoretical predictions, our primary hypothesis is that endogenous prices will be higher in the treatments with collusion than in the treatment without collusion, where this possibility is excluded. Our secondary hypothesis is that buyers will not search (or search little) in all treatments.

As the theoretical predictions are the same for treatments $T10$, $T20$ and $T30$, one may wonder why we introduce different positive probabilities for the collusion. There is a large literature showing that subjects in probabilistic environments often make choices that differ from those predicted by Bayesian updating and expected utility maximization. In particular, conditional probabilities can depend on priors in ways that are inconsistent with Baye's law.[12] Thus, there are reasons to believe that search decisions { and consequently rational price posting { may depend on the exogenous collusion probability in ways that di er from the model's predictions.

A pre-study plan, including a pilot study for the experiment, was posted on the AEA RCT registry on May 17th 2023.[13] The pre-study plan speci es treatments T0, T10 and T20, and we follow the plan in the set-up of hypotheses and signi cance testing. T30 was added to the study at a later stage.

The pilot study was carried out with two matching blocks for T0 and three matching blocks for T20. The average posted price of the sellers was 25 ECU in T0 and 45 ECU in T20, while the variances (between blocks) were 80 and 50, respectively.

Based on the average posted prices and the variances, we calculated the sample size needed to reach a power of 95 percent or better, given a 5 percent signi cance level and a Wilcoxon rank sum test. This estimate was obtained using the method described in Bellemare et al. (2016). The power-threshold required is reached with 6 independent matching blocks per treatment. Data from the pilot is included in the analysis of this paper.

3.3 Data collection

Data were collected in the Research Lab at BI Norwegian Business School in Oslo in the period April 2023 to June 2023. The subjects were recruited from the general student population of the BI Norwegian Business School.[14] Subjects were never exposed to more than one treatment (between-subject design). Recruitment and sub-

[12] See for instance Tversky and Kahneman (1971), Kahneman and Tversky (1972), Ouwersloot et al. (1998), Charness and Levin (2005), and Abs-Ferrer and Garagnani (2023)

[13] See https://www.socialscienceregistry. org/trials/11401.

[14] We argue that behavior in our sample is representative for decision makers in market contexts. Mounting evidence shows that behaviors in convenience samples (CSs) are generally representative of the general population; of students who do not self-select into lab experiments; and of workers in online labor markets, such as Mechanical Turk (see Snowberg and Yariv (2021)). In addition, behaviour in CSs often compares well with that of professionals, such as traders and managers (see Fechette (2016) and Ball and Cech (1996)). Taking this research into account, we believe that our results are informative of a mechanism that may also be important in real posted price markets.

ject management were administered through ORSEE (Greiner, 2015). On arrival, subjects were randomly assigned to cubicles (to break up social ties). Written instructions were handed out and read aloud by the administrator (to achieve public knowledge of the rules). A complete set of instructions is provided in the supplementary online materials. All decisions were taken anonymously on a network of computers.

At the end of a session, subjects were privately paid the sum of ECU earned in two randomly drawn games and a show-up fee of 40 ECU to protect against negative payments.[15] The exchange rate was 1 ECU = 2 NOK in all treatments. The protocol was implemented in zTree (Fischbacher, 2007). In total, 192 participants participated in experiment sessions lasting on average one hour and earned on average 347 NOK.

4 Experimental results

All the results presented exclude data from the first 20 games of the experiment.[16] Furthermore, we exclude prices from games in which the price was set exogenously.

We start by comparing aggregate results from treatments with collusion (treatments T10, T20 and T30) with the treatment without collusion (treatment T0). In the treatments in which there was a positive probability of collusion ($x > 0$), prices posted by subjects are significantly higher than in the treatment without collusion, see table 2. In particular, posted prices in treatments T10, T20 and T30 are on average 14.85 ECU higher than posted prices in treatment T0. This is close to the theoretically predicted difference of 18.1 ECU.

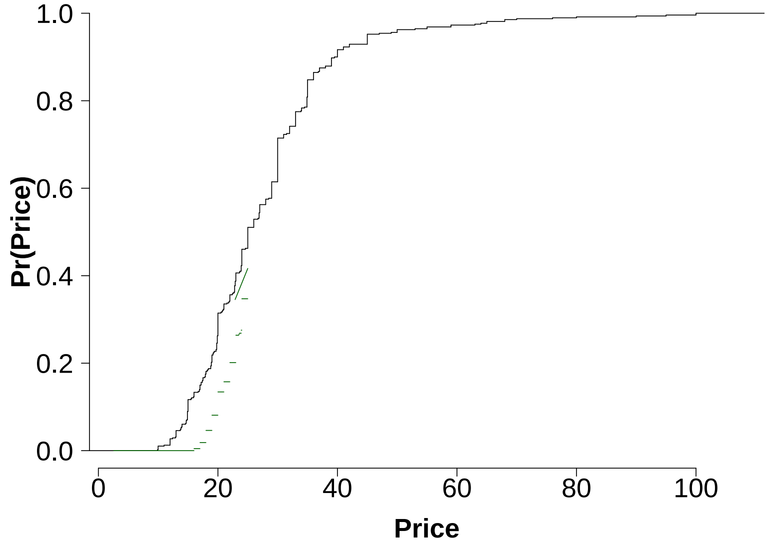
[15] A buyer's payoff in a game is negative in the case she searches while both sellers charge a price equal to 100.

[16] This data selection procedure is in accordance with our pre-study plan. Including the first 20 games does not impact our main results, see appendix B.

Table 2: Regression

	Posted Price
constant	27.62

Figure 3: Price distribution by treatment



Note: First 20 games and games were the price was set exogenously are excluded.

Figure 4 shows the average posted prices by treatment. The average posted price in treatment T0 is 27.6 ECU, which is close to the theoretical prediction of 24.4 ECU. The average prices in treatments T10, T20 and T30 are 32.3, 41.8, and 55.5 ECU, respectively. The average price in treatment T20 is close to the theoretical prediction of 42.6 ECU. Comparing posted prices across treatment we note that the differences between T0 and T20 and between T0 and T30 are statistically significant,

Table 4: Share of price proposals in different ranges in treatments $T10$, $T20$ and $T30$

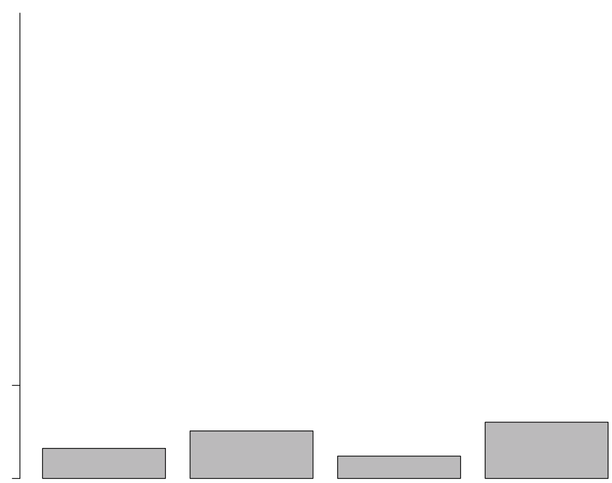
Treatment	$p \in [0; 26.5)$	$p \in [26.5; 62.6]$	$p \in (62.6; 70)$	$p = 70$	$p \in (70; 100]$
$T10$	0.43	0.49	0.00	0.06	0.01
$T20$	0.11	0.75	0.02	0.10	0.03
$T30$	0.14	0.31	0.12	0.39	0.04

Note: First 20 games and games were the price was set exogenously are excluded.

4.2 Search

Figure 5 presents the average search rates by treatment. Search rates are low in all treatments, with rates of 0.06, 0.1, 0.05 and 0.12 in treatments $T0$, $T10$, $T20$ and $T30$, respectively. Although buyers search little on average, this represents a deviation from the theoretical no-search prediction. The differences in search behavior across treatments are not statistically significant.[21].

Figure 5: Share of buyers who search across treatments



Note: First 20 games are excluded.

Tables 5 and 6 present the empirical search frequencies for different price ranges. We first note that search never takes place for price proposals below the support of the

21

equilibrium price proposals. For the remaining price ranges, search decisions deviate from equilibrium predictions in some cases. Considering treatment T0, we note that buyers search too little for off-path price proposals: Only a share of 0.65 decide to search when observing a price in excess of the upper bound of the equilibrium price distribution (but still almost 2/3 of the buyers do). In treatment T10 we note that a relatively high share (0.28) of the consumers decide to search following a price proposal of 70 ECU. Moreover, a higher share than in the other treatments search

For treatment T0, the implied reservation price is the price at which the expected price reduction by searching is equal to the search costs. For treatments T10, T20 and T

4.4 Profits and optimal pricing strategy

The previous section's analysis shows that buyers to large degree best respond given the empirical distribution of prices. In this section, we examine whether sellers make optimal decisions based on the search patterns of buyers and the pricing strategies of of the model. For treatment T30, expected pro ts are more single-peaked. Given these expected pro ts, a strict best response would be to post one particular price in each treatment. However, we believe that this requirement is too strict when evaluating the extent to which sellers' pricing behavior in the laboratory is pro t maximizing. Therefore, we de ne what we call a *reasonable best response* as a price that in expectations yields a payo of at least 75, 80 or 85 percent of the highest expected payo within a treatment. For the 75 percent cut, this implies that any price that in expectations results in a payo of at least 39.1, 44.2, 60.3, and 101.8 in treatments T0, T10, T20 and T30 respectively, constitutes a reasonable best response. Table 9 reports the share of posted prices that are within the range of a reasonable best response in the four treatments.

Table 9: Share of posted prices within the range of a reasonable best response across treatments and for di erent de nitions

De nition of reasonable best response	T0	T10	T20	T30
≥ 75%	0.91	0.93	0.95	0.63
≥ 80%	0.87	0.90	0.94	0.62
≥ 85%	0.78	0.86	0.66	0.58

Note: First 20 games and games were the price was set exogenously are excluded.

3m-2754(jornstpa)27lFor all 6seasotn(p0c.39)]Ta17.5 /F 0 -21.669 Tdf67(all)-310(withinen)2honse imp(and)-310(ras013)-

formalise this notion we use the much used reinforcement learning model developed by Roth and Erev (1995) and Erev and Roth (1998).[24]

In the reinforcement learning model it is assumed that each action in a round of the game is associated with an *attraction*. The attraction of an action then determines the probability at which the action is played. The attraction of a given action depends on historical payoffs associated with that action along with an initial attraction. The initial attraction is estimated along with the subject's sensitivity to attraction with respect to actions and their tendency to forget. In estimating the model we make the structural assumption that subject cannot learn from rounds where the price is set exogenously. Estimates together with actual play can then be used to predict choices.[25]

Table 10: Predicted fraction of price proposals in different ranges in the first game in treatments T10, T20 and T30

Treatment

subjects learn.

5 Conclusion

In this paper, we explore the impact of possible collusion on equilibrium prices, both theoretically and experimentally. The theoretical model suggests that fear of collusion a ects consumer search behavior, reducing the incentive to search further after encountering a high price. This behavior allows non-colluding sellers to set higher prices. In the laboratory experiment, we vary the probability of collusion within treatments. Qualitatively, our results align reasonably well with the theoretical predictions, showing an increase in average prices with potential collusion. Despite some deviations from theoretical expectations, both buyers and sellers demonstrate strong best-response behavior. The discrepancies are to some extent attributed to subjects'

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A Model extension

A.1 Many sellers

Suppose that there are n 2 sellers in the market. The structure of the equilibrium is unaltered.

Consider the no-search equilibrium. The probability that all other sellers have set p^M is equal to $^{n \; 1}$. Consider a seller who sets p 2 $[p_0; p_1]$. We want to nd the probability that this seller will attract informed buyers. Consider a random competitor. The probability that this competitor sets a price above p is $+ (1 \quad)(1 \quad F(p))$. The probability that all the sellers set a price above p is thus $[\; + (1 \quad)(1 \quad F(p))]^{n \; 1}$.

Pro ts when setting p 2 $[p_0; p_1]$ can be written as

$$(p) = p \;\; u + [\; + (1 \quad)(1 \quad F(p))]^{n \; 1} l \tag{14}$$

At the interval $[p_0; p_1]$, pro t must be equal, which implies that

$$p \;\; u + [\; + (1 \quad)(1 \quad F(p))]^{n \; 1} l \;\; = p_1(u + \;\; ^{n \; 1} l)$$

We solve out for $1 \quad F(p)$ and get that

$$1 \quad F(p) = \frac{\left[\frac{(p_1 \quad p)u + p_1 \;\; ^{n \; 1} l}{pl}\right]^{\frac{1}{n \; 1}}}{1} \tag{15}$$

The equilibrium candidate without search can be written as

1. Equal pro t when setting p^M and p_1:

$$p^M(u + \;\; ^{n \; 1}\frac{l}{n}) = p_1(u + \;\; ^{n \; 1} l) \tag{16}$$

2. Equal pro ts for all p 2 $[p_0; p_1]$, $F(p)$ given by (15). As above p_0 is de ned by $F(p_0) = 0$.

3. Consumers are indifferent between searching and not searching at p_1

$$(1 \quad) \int_{p_0}^{p_1} F(p)dp = c \tag{17}$$

If the solution to (17) is greater than 1, then $p_1 = 1$.

Note that the equation for p_1, (17), has the same form as with two firms. This reflects the fact that the searching worker only visits one more firm.

Let us derive conditions for consumer search at p^M. Given that a consumer observes a price p^M, the conditional probability that collusion takes place is given by $x^M = \frac{x}{x+(1 \quad x)}$ (by Bayes law), as before. And as before, the gain from search is $(1 \quad)((1 \quad)(p^M \quad p_1))$ higher than the gain from search at p_1. Hence, the condition for no search is still given by (5).

Consider then the equilibrium candidate with consumer search, with q still denoting the probability that the buyer searches at p^M. The profit of a seller posting $p \in [p_0; p_1]$ is then stil given by (14), but with u replaced by $\tilde{u} = u(1 + (1 \quad n) q)$. Hence the equilibrium candidate with search can be written as

1. Equal profit when setting p^M and p_1:

$$p^M (u(1 \quad q) + I \quad ^n \ ^1 = n) = p_1(u(1 + (1 \quad n)q \ ) + \quad ^n \ ^1 I \ ) \tag{18}$$

2. Equal profits for all $p \in [p_0; p_1]$, implying that $F(p)$ is given by (15) with u replaced by $u(1 + (n \quad 1) q)$. p_0 is defined by $F(p_0) = 0$.

3. Consumers at p_1 are indifferent between searching and not searching, satisfying (10). If the solution to (10) is greater than 1, then $p_1 = 1$

4. Consumers at p^M are indifferent between searching and not searching, satisfying (11)

A.2 Stochastic collusion price

We retain the assumption that rms collude with probability x. However, we assume that the colluding price is stochastic with distribution $G(p)$. We assume that the distribution is continuous with support $(p^{min}; p^{max})$, p^{max} 1. We assume that $n = 2$ (two sellers).

We consider an equilibrium candidate in which sellers randomise on two intervals $I^N = [p_0; p_1]$ and I^M

with equality if $q(p) > 0$. Equilibrium is a value $\in [0;1]$, two distribution functions $F^N(p)$ and $F^M(p)$ with support I^N and I^M, respectively, and a function $q(p)$ on I^M, satisfying the following conditions:

1. Equal pro ts for all $p \in [p_0; p_1]$ implying that $F^N(p)$ given by

$$1 \quad F^N(p) = \frac{u(p_1 \quad p)}{p\tilde{\Gamma}} \tag{21}$$

   where p_0 is de ned by $F^N(p_0) = 0$.

2. All prices in the support of F^M give the same pro ts to the seller, and this pro t is equal to the pro t if a price is set in I^N: $^M(p) = {}_1$ for all $p \in I^M$.

3. Uninformed consumers are indi erent between searching and not searching at p_1:

$$(1 \quad) \int_{p_0}^{p_1} F(p)dp = c \tag{22}$$

4. When observing a price $p \in I^M$, uninformed consumers are 1) either indi erent between searching and not searching (if $q(p) < 1$) or prefer not to search (if $q = 1$). That is, (20) is satis ed with complimentary slackness.

Let us make some observations. First, F^M has no mass points. Suppose that it had a mass point at p^0. Then since G is without mass points, the posterior probability that there is collusion at p^0 is 0, and the consumers will search with probability 1.

I^N

We cannot rule out that consumers don't search at the top of I^M. If so, consumers' search behaviour will not follow a reservation price property (i.e., that consumers search if and only if the observed price is above a certain threshold).

Suppose then that there may be overlap between I^M and I^N. Consider price setting at I^N. Sellers, when setting the price, know that there is no collusion, and hence. For su ciently low prices, consumers do not search. Hence the distribution F^N is determined by (21), as before. Consider p_1, the highest price at F^N. Let denote the fraction of sellers who set a higher price. At p_1 we have that $z(p_1) = \frac{xg(p_1)}{\;}$

xg(p1 +) J/F65 7.9701 Tf 6.105 0 Td [(z)f

B Results

B.1 Inference: Last 20 games

Table 11: Wilcoxon rank-sum test (p-values): Posted price

	T0	T10	T20	T30
T0				
T10	0.394			
T20	0.009	0.026		
T30	0.004	0.009	0.132	

Note: First 20 games and games were the price was set exogenously are excluded.

Table 12: Wilcoxon rank-sum test (p-values): Share of posted prices at 70 ECU

	T0	T10	T20	T30
T0				
T10	0.003			
T20	0.004	0.090		
T30	0.004	0.012	0.009	

Note: First 20 games and games were the price was set exogenously are excluded.

Table 13: Wilcoxon rank-sum test (p-values): Share who search.

	T0	T10	T20	T30
T0				
T10	0.406			
T20	0.256	0.091		
T30	0.101	0.809	0.075	

Note: First 20 games are excluded.

Table 14: Kolmogorov-Smirnov Test (p-values): Price distribution.

	T0	T10	T20	T30
T0				
T10	1.871e-07			
T20	$<$ 2.2e-16	$<$ 2.2e-16		
T30	$<$ 2.2e-16	$<$ 2.2e-16	$<$ 2.2e-16	

Note: First 20 games and games were the price was set exogenously are excluded.

Table 15: Kolmogorov-Smirnov Test (p-values): Price distribution conditional on price being below 70 ECU.

	T0	T10	T20	T30
T0				
T10	1.042e-06			
T20	< 2.2e-16	< 2.2e-16		
T30	< 2.2e-16	< 2.2e-16	< 2.2e-16	

Note: First 20 games and games were the price was set exogenously are excluded.

B.2 Results and inference: All games

Table 16: Treatment measures by treatment

	Average price	Share of posted prices at 70 ECU	Share who search
T0	32.6	0.01	0.091
T10	37.3	0.8	0.135
T20	45.7	0.10	0.097
T30	53.7	0.31	0.135

Note: Games were the price was set exogenously are excluded from average price and share of posted prices at 70 ECU.

Table 17: Wilcoxon rank-sum test (p-values): Posted price

	T0	T10	T20	T30
T0				
T10	0.310			
T20	0.004	0.064		
T30	0.002	0.041	0.485	

Note: Games were the price was set exogenously are excluded.

Table 18: Wilcoxon rank-sum test (p-values): Share of posted prices at 70 ECU

	T0	T10	T20	T30
T0				
T10	0.012			
T20	0.005	0.172		
T30	0.005	0.013	0.012	

Note: First 20 games and games were the price was set exogenously are excluded.

Table 19: Wilcoxon rank-sum test (p-values): Share who search.

	T0	T10	T20	T30
T0				
T10	0.065			
T20	0.520	0.228		
T30	0.077	0.699	0.149	

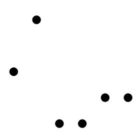
Note: First 20 games are excluded.

B.3 Results by round

Figure 7: Average price by game and treatment

Note: Games were the price was set exogenously are excluded.

Figure 8: Search behavior by game and treatment



C Learning model

The model of reinforcement learning assumes that each action in a round of the game is associated with an *attraction*. The attraction of an action then determines the probability at which the action is played. For sellers, we let $A_i^{Seller}(t)$ denote the attraction of posting a price in the range P_i in round t. The attraction for sellers associated with a price range P_i is updated according to the following rule

$$A_i^{Seller}(t) = \begin{cases} {}_{Seller}A_i^{Seller}(t-1) + (t) & \text{if } p(t) \in P_i \\ {}_{Seller}A_i^{Seller}(t-1) & \text{otherwise} \end{cases} \quad (23)$$

where (t) is the realised payo in round t and $_{Seller}$ is the recency parameter. The probability of posting a price in range P_j is then

$$Pr_i(t) = \frac{\exp(\ _{Seller} A_j^{Seller}(t \quad 1))}{P \exp(\ _{Seller} A_i^{Seller}(t \quad 1))} \tag{24}$$

where $_{Seller}$ represents sensitivity to attraction.

When tting the model we consider ve di erent price ranges: $[0;26:5)$, $[26:5;62:6]$, $(62:6;70)$, 70 and $(70;100]$.[26] We estimate initial attraction $A_i^{Seller}(0)$, $_{Seller}$, and $_{Seller}$, where $A_i^{Seller}(0)$ is normalised to zero for the lowest price range ($[0;26:5)$).

The model estimates are presented in tables 20. The recency parameters indicate that learning is not to

D Heterogeneity

Our main analysis focuses on aggregated results. In this section we look closer at heterogeneity in price decisions across subjects. We display the distribution of two di erent measures: Average price across games by subject and share of posted prices at 70 ECU across games by subject.

D.1 Average price

Figure 9 presents the distribution of average price by subject across our four treatments. As the gure shows, there is heterogeneity in average pricing behavior of subjects. Average prices range from 16.9 ECU to 47.1 ECU in treatment T0; from 23.1 ECU to 67.8 ECU in treatment T10; from 29.6 ECU to 78.6 ECU in treatment T20; and from 30.5 ECU to 100 ECU in treatment T30.

Figure 9: Distribution of average price by subject.

Note: Bin size=5. First 20 games and games were the price was set exogenously are excluded.

D.2 Share of posted prices at 70 ECU

Figure 10 presents the distribution of the propensity to post a price of 70 ECU by subject across our four treatments. As the figure shows, the propensity to post a price of 70 ECU is far from evenly distributed across subjects. In treatments T10 and T20 half the subjects or more never post a price of 70 ECU. In treatment T30, however, more than half of the subjects post a price of 70 ECU at least twice.

Figure 10: Distribution of propensity to post a price of 70 ECU by subject.

Note: Bin size=0.1. First 20 games and games were the price was set exogenously are excluded.