

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's 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

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1 Introduction

Collusion may take place in various markets. For instance, the gasoline market in several countries is known for anti-competitive behaviour among sellers.¹ Similarly, the grocery market has a questionable reputation regarding collusion.² In these markets, there are good reasons to believe that consumers are cognizant that sellers may be colluding. In this paper, we investigate whether *possible collusion*, interpreted as a positive prior probability that collusion occurs, may lead to higher prices even if collusion does not actually take place.

The mechanism through which this occurs is related to consumer search. If sellers set prices too high, buyers will search for a better price, and this disciplines sellers when setting prices. However, the risk of collusion undermines this mechanism, as collusion leads to correlated prices among different sellers. Therefore, one might conjecture that a risk of collusion results in an increase in prices.

In the first part of our paper, we explore this mechanism in a theoretical model of consumer search based on the [Stahl \(1989\)](#) framework, although the same mechanism is present in the [Burdett and Judd \(1983\)](#) model (see the discussion section for details). In our model, a subset of the buyers have limited information about the prices set by different sellers and can gather more information about prices through costly search. There is an exogenous probability that sellers may collude and set a high price, higher than the reservation price of buyers in the absence of possible collusion. In the presence of possible collusion, a buyer who observes the high price does not know if the price is high because the seller in question follows a high-price strategy, in which case it is optimal to search, or if the price is high because the sellers collude, in which case it is not. Therefore, an *a priori* positive probability of collusion will reduce the incentives of buyers to continue searching after observing a high price, and reduce the probability of search. Some of the sellers will exploit this and set a high

¹See for instance [Clark and Houde \(2013\)](#), [Foros and Steen \(2013\)](#), [Byrne and De Roos \(2019\)](#), and [Assad et al. \(2024\)](#) for studies on anti-competitive behaviour in gasoline markets.

²In the UK the market has been scrutinized by the Competition and Markets Authorities on several occasions. For example, Sainsbury's and Asda were fined £116 million in 2007 for price fixing (see <https://www.theguardian.com/business/2007/dec/08/supermarkets.asda>), and supermarkets are continuously probed over prices (see <https://www.bbc.com/news/business-65601292>). In the US, in the wake of a recent Federal Trade Commission report ([FTC, 2024](#)), Democratic lawmakers have requested investigations into grocery store chains for price manipulation (see article in Time Magazine <https://time.com/6977026/democrats-biden-executive-authority-grocery-prices>).

price using possible collusion as a "disguise" for a high seller-specific price. Since prices are strategic complements, this will give rise to "multiplier effects" and induce all sellers to set higher prices. As a result, the entire price distribution shifts up, and there is a substantial increase in average prices.

In the second part of the paper, we empirically investigate the mechanism analysed in the model by conducting a series of laboratory experiments. Laboratory experiments are well-suited for studying the effects of possible collusion. First, collusion is challenging to observe in real markets, and a fear of collusion is even more difficult to observe. In a controlled laboratory setting, the possibility of collusion can be introduced through a publicly known probability distribution. Second, in the lab we have full control of the information set of all buyers, which would be difficult to measure in field data.

In the experiment, we implement an environment identical to that of the model: Participants are either sellers or buyers. Sellers set prices simultaneously, and each buyer observes one price and can choose whether to continue searching or not. As in the model, there is a probability that sellers collude, in which case prices are set exogenously at a known level p^M for all sellers. We perform 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 outcomes according to our model are the same in these three treatments.

Without possible collusion, the results are more or less spot-on compared with theory. In the three treatments with a positive probability of collusion, there is 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 align with the theory. When we compare the average posted prices in the treatments with possible collusion to the treatment without it, we observe an increase of 54%, from 27.62 to 42.47 units. The predicted average posted price increases by 75%, from 24.4 to 42.6 units. Regarding search behaviour, we find that search rates are low across all treatments, which is consistent with our theoretical predictions.

The price averages over treatments conceal differences between the treatments with possible collusion that are inconsistent with the theory. Prices are higher than predicted in the $T30$ treatment and lower than predicted in the $T10$ treatment (with 30 and 10 percent

probability of collusion, respectively). We investigate the deviations from equilibrium predictions using a reinforcement learning model which we estimate. We find that variations in participants' initial beliefs across treatments can help explain these deviations.

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.

We conclude that our hypothesis that possible collusion influences prices even in the absence of actual collusion is supported, both by our model and by our experiment. The next question then is for which markets our theory may be relevant. Criteria for a market to be relevant may include that 1) sellers post prices, 2) buyers search over prices (or at least have the option to do so), 3) collusion between sellers may take place, and 4) consumers are cognizant that collusion may take place.

The first two criteria are satisfied for most retail markets. Some retail markets, such as the gasoline market and the food market, also satisfy 3) and 4). In addition, 3) and 4) may also be satisfied when consumers suspect collusion between producers of consumer goods, which may happen for a wide range of products. For recent examples, see [Miller et al. \(2021\)](#), who analyse collusion among beer producers in the U.S., [Aryal et al. \(2022\)](#), who analyse coordinated capacity reduction in the airline industry in the U.S., [Bertomeu et al. \(2021\)](#) who study tacit collusion in the automotive industry in the U.S., and [Igami and Sugaya \(2022\)](#) who analyse the international vitamin cartel. Fear of collusion may also arise if consumers suspect hub-and-spoke collusion involving both producers and retailers, see [Clark et al. \(2024\)](#) who document hub-and-spoke collusion between retailers and bread producers in Canada. Finally, as pointed out by [Harrington \(2005\)](#), consumer suspicion may, rightfully or not, emanate from unusual pricing practices, such as unexpected and/or parallel price increases.

Related Literature

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

In the literature on price posting and consumer search with learning consumers typically do not know the costs of the different sellers (see, e.g., [Benabou and Gertner \(1993\)](#) and [Dana Jr \(1994\)](#) for early contributions).³ [Janssen et al. \(2011\)](#) and [Janssen et al. \(2017\)](#) introduce cost uncertainty to the [Stahl \(1989\)](#) model with consumer search, and show that such uncertainty raises prices for both informed and uninformed consumers.⁴ 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 different, in our model prices are uncertain because of possible collusion, not because of uncertain costs. In addition to being conceptually different, this makes our model much more tractable, and eliminates the need for equilibrium refinements.

Our fear of collusion mechanism is related to a search discouragement mechanism in concurrent work by [Grubb and Westphal \(2024\)](#). They independently develop a consumer-search model in which multi-brand firms set the same prices, and consumers are uncertain as to whether the firms are multi-brand or not. Although the mechanisms in the two papers are related, the applications are very different, and therefore we consider the papers to be complementary. We also explore our mechanism in the lab, which they do not.

Our paper contributes to the experimental literature on posted-offers models with price dispersion. [Cason et al. \(2003\)](#) and [Cason et al. \(2021\)](#) examine the noisy sequential search model of [Burdett and Judd \(1983\)](#); [Cason and Datta \(2006\)](#) and [Cason and Mago \(2010\)](#) examine the sequential search model of [Robert and Stahl \(1993\)](#) with advertising; [Helland et al. \(2017\)](#) examine the capacity constraints model of [Lester \(2011\)](#); [Morgan et al. \(2006\)](#) examine the simultaneous pricing model of [Varian \(1980\)](#), while [Heggedal et al. \(2024\)](#) study sequential pricing in this framework.⁵

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

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

⁵There also exists a literature that investigates different aspects of the [Diamond \(1971\)](#) paradox in the

The zest of this literature is that the comparative statics results of average prices obtained in the experiments are in line with equilibrium predictions, but not necessarily the average price level (see [Cason and Mago \(2010\)](#)).⁶ In our experiment, with complex search markets, both comparative statics results and average prices are broadly in line with theoretical predictions.

There is a literature on consumer search and collusion in repeated games; see [Nilsson et al. \(1999\)](#), [Campbell et al. \(2005\)](#), [Petrikaitė \(2016\)](#), [Montag and Winter \(2020\)](#), and [Shadarevian \(2022\)](#) for theoretical contributions, and [Orzen \(2008\)](#) and [Moellers et al. \(2016\)](#) for experimental evidence.⁷ A common characteristic of these studies is that buyers know the state of the game. In contrast, in our paper, buyers form beliefs about whether collusion takes place or not, and these beliefs affect consumers’ incentives to search.⁸

Organisation of the paper

The remainder of the paper is organized as follows. In section 2, we outline the theoretical framework and provide a general characterization of equilibria. In section 3, we give a detailed description of equilibrium in which buyers do not search. In section 4, we present our experimental design and procedures, and in section 5, we report the results of our experiment. In section 6, we discuss how the model can be expanded to allow for a stochastic collusion price and to include more than two sellers. We also explore the effects of possible collusion in the [Burdett and Judd \(1983\)](#) framework, and examine the policy implications of our findings. Finally, section 7 offers a brief conclusion.

lab. See, for instance, [Grether et al. \(1988\)](#), [Davis and Holt \(1996\)](#) and [Abrams et al. \(2000\)](#).

⁶Moreover, at an individual level prices are autocorrelated (see [Cason et al. \(2003\)](#) and [Cason et al. \(2021\)](#)).

⁷There is a large experimental literature on collusion in repeated price-setting games without price-information frictions. See [Potters and Suetens \(2013\)](#) and [Harrington Jr et al. \(2016\)](#) for excellent surveys.

⁸[Harrington Jr and Ye \(2019\)](#) also include an exogenous probability of seller collusion in consumers’ beliefs. In their model, sellers coordinate prices through advertisements of non-binding list prices. They find that collusion between sellers may take place *despite* consumers’ fear of collusion. In our model, in contrast, fear of collusion increases prices when collusion in fact does not occur.

2 Model

Our starting point is the Stahl model of consumer search. Two sellers post prices simultaneously and independently (see the discussion section for an extension to $n \geq 2$ sellers). Their unit costs are normalised to zero. There is an arbitrary number of buyers with a maximum willingness to pay for the good normalised to 1.

There are two types of buyers. Informed buyers know the posted prices and buy from the seller with the lowest price if this is less than or equal to 1 (if there is a tie, they randomise between the sellers). Uninformed buyers approach one seller at random and get a price quote. They can choose to search again at cost $c < 1$ to get a second price quote. Let u denote the number (measure) of uninformed buyers per seller and I the number (measure) of informed buyers. All agents are risk neutral.

In the unique Stahl equilibrium, the sellers play with mixed strategies and randomise over an interval $[p_0, p_s]$ with the same distribution function $F(p)$. The highest price p_s is determined so that uninformed buyers are indifferent to searching for a new price quote or not and choose not to search. Hence, there is no search in equilibrium.

We extend the model by assuming that with an exogenous probability x , the sellers collude on prices, and set a price $p^M > p^s$ (in the discussion section we extend the model to incorporate a stochastic collusion price). Buyers know that there is an *ex ante* probability x that collusion will take place, but they do not know if the sellers actually collude or not. We will derive the equilibrium of the model when collusion does not occur (when collusion occurs, the sellers trivially set $p = p^M$).

We first notice that with possible collusion, the Stahl equilibrium is no longer an equilibrium. Suppose it was, and suppose that a seller deviates and sets $p^M > p_s$. Consider an uninformed buyer who visits this seller. Given the equilibrium strategies of the sellers, Bayesian updating implies that the probability of collusion is 1. It follows that the buyer accepts the price offer and buys, and the deviation is profitable. Hence, the Stahl equilibrium unravels. It follows that in any equilibrium, sellers set p^M with strictly positive probability. Note also that if a buyer observes a price $p \neq p^M$, the buyer knows that collusion does not take place, and therefore updates the probability of collusion to 0.

Below we will focus on a subclass of equilibria in which buyers do not search in equilibrium, as in the Stahl equilibrium. However, for completeness we will first give a general characterisation of the equilibrium.

Proposition 1. *An equilibrium of the pricing game described above exists and has the following structure:*

1. *Sellers play with identical mixed strategies as follows (with $\rho + \rho_b + \rho_s = 1$):*
 - (a) *With probability $\rho \in (0, 1)$, a seller sets the price p^M .*
 - (b) *With probability $\rho_s \in (0, 1)$, a seller randomises on an interval $[p_0, p_1]$, where $p_1 < p^M$.*
 - (c) *With probability $\rho_b \in [0, 1)$ (which is zero in all our applications), a seller randomises on an interval $[p_2, p^M)$, where $p^2 \in (p^1, p^M)$.*
2. *Uninformed buyers' search behaviour after the first draw (informed buyers always buy from the seller offering the lowest price):*
 - (a) *If the price is p^M , the buyer searches with probability $q \in [0, 1)$.*
 - (b) *If the price is in the interval $[p_0, p_1]$, the buyer does not search. At p_1 , the buyer is indifferent between searching and not.*
 - (c) *If the price is in the interval $[p_2, p^M)$, the buyer searches with probability 1.*

A formal proof is given in Appendix A.1.⁹ Here we will provide some arguments as to why the equilibrium has this structure.

We have already argued that $\rho > 0$. We cannot have $\rho = 1$. If so, a seller who deviates and posts $p = p^M - \epsilon$ will attract all informed buyers and increase its profit. Next, below p^M , the distribution of the posted prices cannot have a mass point. This follows from the standard undercutting argument of Varian (1980) and others: If there is a mass point at $p' < p^M$, a seller would have an incentive to set a price equal to $p' - \epsilon$ and attract informed buyers with a probability strictly higher than at p' .

⁹In the appendix we use the notation (ρ_0, ρ_1, ρ_2) instead of (ρ, ρ_b, ρ_s) . We do this separation to simplify the notation in the main text, where we concentrate on the case with $\rho_b = 0$ and write $1 - \rho$ instead of ρ_s .

Since there is a strictly positive cost associated with searching, there must be a strictly positive gain from search in order for buyers to do so. Hence, there must exist an interval at the lower end of the price distribution, which we denote $[p_0, p_1]$, at which the buyers do not search. The standard argument from [Varian \(1980\)](#) implies that the interval is connected. Furthermore, at p_1 the buyer must be indifferent between searching and not searching. In the appendix we also show that $p_1 < p^M$.

Finally, we cannot rule out that sellers may set prices at an interval $[p_2, p^M)$, at which uninformed buyers search, and sell to informed buyers and searching uninformed buyers in the case that the opponent sets an even higher price.

3 No-search equilibrium

In our experiment, we will study a parameterization of the model in which the buyers do not search in equilibrium. That is, an equilibrium where $q = 0$ at p^M and $\rho_b = 0$. The reason for this choice is that our benchmark is the Stahl model (that is, $x = 0$ in our model) in which there is no search in equilibrium. We have designed the experiment to facilitate a comparison of prices holding search behaviour constant. Moreover, the effect on expected price when going from $x = 0$ to $x > 0$ is larger in equilibria without search. Thus, while there in theory always will be an effect on expected price when going from $x = 0$ to $x > 0$, our chance of actually identifying an effect if there is one, is greater if we study a parameterization of the model in which the buyers do not search.

We start by imposing the requirement that buyers do not search in equilibrium and derive the resulting equilibrium candidate. We then derive conditions under which the no-search equilibrium candidate is indeed an equilibrium, and conditions under which it is unique.

The profit of a seller that sets a price at or below p_1 is

$$\pi = p[u + \rho I + (1 - \rho)I(1 - F(p))] \tag{1}$$

Equation (1) states that the profit of a seller 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 buyers, and to

all the informed buyers if the opponent sets a price either equal to p^M (which happens with probability ρ) or in the interval $[p_0, p_1]$ but above p (which happens with probability $(1 - \rho)(1 - F(p))$).

The gain from search at p_1 is given by $(1 - \rho) \int_{p_0}^{p_1} F(p) dp$. The first factor reflects 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 $\rho \in (0, 1)$ and a distribution $F(p)$ with support $[p_0, p_1]$ satisfying the following conditions:

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

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

2. Equal profits for all $p \in [p_0, p_1]$, implying that $F(p)$ is given by

$$1 - F(p) = \frac{(u + \rho I)(p_1 - p)}{pI(1 - \rho)} \quad (3)$$

where p_0 is defined by $F(p_0) = 0$.

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

$$(1 - \rho) \int_{p_0}^{p_1} F(p) dp = c \quad (4)$$

Note that the lower part of the equilibrium is identical to the equilibrium of the Stahl model with $\tilde{u} = u + \rho I$ uninformed customers per seller and $\tilde{I} = (1 - \rho)I$ informed buyers, and with search costs $c' = c/(1 - \rho)$. In particular, it follows that since $\rho > 0$, $p_1 > p_s$.¹⁰

Finally, in Appendix A.3 we show the following proposition:

Proposition 2. *The equilibrium candidate without consumer search exists and is unique.*

¹⁰The undercutting argument in Varian (1980) implies that if, contrary to our assumption, $p_s > p^M$, there will not be a mass point at p^M , as the sellers will then have an incentive to deviate and undercut p^M slightly. So in this case possible collusion has no bite.

It should be noted that in the no-search equilibrium candidate, *the price distribution is independent of x* (the probability that collusion takes place). When sellers set prices, they *know* that collusion does not occur. When buyers observe a price different from p^M , they also know that collusion does not occur. Only if buyers observe p^M , they are uncertain whether collusion has taken place or not. However, by assumption, buyers do not search when observing p^M , and hence their beliefs do not influence equilibrium. However, as will be clear in the next subsection, x will influence the incentives to search at p^M and thus whether or not the no-search equilibrium candidate is an equilibrium of the model.

3.1 Existence and uniqueness of the no-search equilibrium

In this subsection, we will derive conditions under which the equilibrium candidate without consumer search is an equilibrium of the model, and under which it is the unique equilibrium. From Proposition 1 it follows that search can take place in equilibrium for prices just below p^M , and at p^M . We will derive conditions under which this will not happen.

Consider first firm incentives to post prices just below p^M . A seller does not have incentives to set a price p^{M-} (just below p^M) whenever

$$p^M ((1 - q)u + \rho qu + \rho I/2) \geq p^M \rho ((1 + q)u + I),$$

or

$$(1 - q - \rho)u \geq \rho I/2 \tag{5}$$

Hence, the equilibrium candidate with no search at p^M ($q = 0$) is consistent with $\rho_b = 0$ whenever

$$u \geq \frac{\rho}{1 - \rho} I/2 \tag{6}$$

In this subsection we assume that (6) is satisfied.

Consider next incentives to search at p^M . Given that a buyer observes a price p^M , the conditional probability that collusion takes place is given by (from Bayes' law)

$$x^M = \frac{x}{x + (1 - x)\rho} \tag{7}$$

The complementary probability (that collusion does not occur) is $1 - x^M = \frac{(1-x)\rho}{x+(1-x)\rho}$.

Consider the case where collusion does not take place. We compare the gain from search at p_1 and p^M . If the other seller sets p^M , the gain from search is zero both at p_1 and p^M . Otherwise, the gain from search is $p^M - p_1$ higher at p^M than at p_1 . The expected gain from search is equal to c at p_1 , since the buyer at p_1 is indifferent between searching and not. Hence, for there to be no search at p^M , we must have that

$$(1 - x^M) (c + (1 - \rho)(p^M - p_1)) \leq c \quad (8)$$

or that

$$\frac{(1 - x)\rho}{x + (1 - x)\rho} \leq \frac{c}{c + (1 - \rho)(p^M - p_1)} \quad (9)$$

The left-hand side, the probability that there is no collusion given that the buyer observes p^M , is strictly decreasing in x for a given ρ , and is 1 for $x = 0$ and 0 for $x = 1$. Recall that the equilibrium values of ρ and p_1 are independent of x when there is no consumer search. Hence, for any equilibrium values (ρ^*, p_1^*) there exists a value \bar{x} such that (9) is satisfied whenever $x \geq \bar{x}$

Proposition 3. *Suppose (6) is satisfied. Let the no-search equilibrium candidate value ρ^* be given. Then there exists a unique value $\bar{x} \in (0, 1)$ given by (9) with equality, with $\rho = \rho^*$ and $p_1 = p_1^*$, with the following properties: If $x \geq \bar{x}$, there exists a unique equilibrium without consumer search. If $x < \bar{x}$, there exists no equilibrium without consumer search.*

In the equilibrium candidate without search, setting p^M instead of p_1 gives a higher profit per sale, but also reduces the number of sales with $\rho I/2$, and ρ^* induces indifference. Furthermore, ρ^* is independent of the prior probability x of collusion. If x is sufficiently high, the posterior belief that collusion occurs (given ρ^*) is sufficiently high to prevent buyers at p^M from searching.

Note that both the requirement for absence of undercutting at p^M (equation 6) and the definition of \bar{x} include the no-search equilibrium candidate value ρ^* , and are in that sense endogenous. However, ρ^* does not depend on x , and we can write it as a function of the other parameters in the model, which are u, I , and c , $\rho^* = \rho(u, I, c)$, which, when substituted

in, gives the two conditions only in terms of exogenous variables.

Proposition 3 states conditions that ensure that the no-search equilibrium exists and is the unique no-search equilibrium. However, it does not rule out that there exist other equilibria with search. Our next step is to find conditions under which the no-search equilibrium is unique within the class of all equilibria.

To do so, we must ensure that consumers do not search if ρ decreases below ρ^* . As we show in the Appendix, it suffices to show that buyers do not search in p^M for lower values of x when ρ_b is zero. We note that a reduction in ρ increases the updated probability of collusion after observing p^M , see equation (7), and this reduces incentives to search. However, the gain from search, conditional on collusion not taking place, also increases. We need an assumption that ensures that the first effect dominates. This assumption, which we refer to as Assumption 1, is rather technical and is specified in the Appendix A.4.

Assumption 1 For all $\rho \leq \rho^*$, the following inequality is satisfied:

$$\frac{(1-x)\rho}{x+(1-x)\rho} \left(c + (1-\rho) \left(p^M - \frac{c}{1 - \frac{u+\rho I}{(1-\rho)I} \ln \frac{u+I}{u+\rho I}} \right) \right) \leq c \quad (10)$$

Assumption 1 is somewhat hard to penetrate. However, it is not very strong and is satisfied for the parameter choices in the experiment.

In Appendix A.4 we show the following proposition:

Proposition 4. *Suppose $x \geq \bar{x}$, and suppose that (6) is satisfied as well as Assumption 1. Then the no-search equilibrium is the unique equilibrium.*

3.2 Comparative statics results

We will first give comparative statics results in the no-search equilibrium. We will assume that the shifts are sufficiently small so that the equilibrium remains a no-search equilibrium.

Proposition 5. *Suppose $x > \bar{x}$. Then the following is true:*

1. *An increase in p^M increases ρ and increases expected transaction prices.*
2. *An increase in c reduces ρ and reduces expected transaction prices.*

The proof is in Appendix A.5. The last result is surprising, as an increase in c in the absence of possible collusion certainly leads to *higher* (not lower) prices.

To understand the results, first consider an increase in p^M . For a given ρ this increases the profit at p^M while the profit at p_1 is unchanged. In the proof of Proposition 2 we show that, around the equilibrium value ρ^* , an increase in ρ increases profits more at p_1 than at p^M . Hence, to establish equal profits at p_1 and p^M , ρ shifts up, and therefore also equilibrium prices.

An increase in c for a given ρ increases profits at p_1 without affecting profits at p^M . Hence, in order to establish equal profits at p_1 and p^M , ρ must decrease, as this decreases profits more at p_1 than at p^M . But a lower ρ means lower equilibrium profits and lower expected transaction prices (since the total transaction values remain constant).

In Appendix C, we provide numerical simulations of the model where we vary the parameters around those used in the experiment. These simulations demonstrate that the impact of possible collusion on prices can be substantial across a wide range of parameter values.

Our last proposition states some limit results for the equilibrium of our general model.

Proposition 6. *a) As $x \rightarrow 0$, $\rho^* \rightarrow 0$ and the no-search equilibrium does not exist. Furthermore, there exists a value \hat{x} of x such that $\rho_b = 0$ whenever $x \leq \hat{x}$.*

b) As $c \rightarrow 0$, the equilibrium price distribution converges to 0.

In a) the claim that the no-search equilibrium does not exist follows directly from Proposition 2. The rest of the proposition is proved in Appendix A.6.

Result a) is quite intuitive. If ρ^* does not go to zero, buyers at p^M know with a probability converging to 1 that there is collusion, and hence search with probability 1, in which case it is better to set p_1 (see the appendix for details). Furthermore, the sellers at p^{M-} only make sales with positive probability when the other seller sets p^M , so the profit at p^{M-} goes to zero as $x \rightarrow 0$.

Result b) tells us that prices converge to zero when the search cost converges to zero. Hence, prices are continuous in c at $c = 0$.

4 Experimental design and procedures

The aim of the experiment is to investigate empirically the fundamental mechanism of our model. To accomplish this objective, we will compare pricing and searching decisions in two different scenarios: one where pricing is always determined endogenously ($x = 0$), and another where prices may be set exogenously at the collusive level ($x > 0$).

We implement a parameterized version of the model presented in Section 2 in which there is no search in equilibrium to accentuate the difference in price setting. We have four main treatments. In our baseline treatment, $T0$, the price is never set exogenously. In treatments $T10$, $T20$ and $T30$ the probability that the price is set exogenously at p^M is 0.10, 0.20 and 0.30, respectively. The event "collusion" is drawn i.i.d. across games.

In the following, we refer to treatments in which prices may be set exogenously as treatments *with possible collusion*, and the treatment in which prices are never set exogenously as the treatment *without possible collusion*.

4.1 Implementation

Subjects play 40 identical and independent games within a treatment. In each game, four subjects are matched in a market. Two of the subjects play the role of sellers, and two play the role of uninformed buyers. Sellers have zero marginal cost, while buyers have unit demand with a valuation of 100 experimental currency units (ECU). The roles remain fixed throughout the experiment.

The only treatment variation is the probability that the price is set exogenously. At the beginning of each game, a random draw determines whether sellers simultaneously and independently choose a price in the interval $[0,100]$ ECU or the price is set exogenously at 70 ECU for all sellers.¹¹ Both sellers know the realization of the draw while buyers do not.

A buyer observes the price of one of the sellers in his/her market, while the other buyer observes the price of the other seller. Buyers can choose to purchase at the observed price or pay a cost of 20 ECU to observe the price of the other seller in the market as well.¹² This

¹¹We picked 70 to balance two concerns: to have a sufficient distance from the upper bound p_1 , and to have a sufficient distance from 100 to avoid fairness considerations.

¹²The search cost is set at a level that gives flexibility when setting the remaining parameters, in particular

search decision is the only decision of buyers, purchasing is automated. 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.¹³

The concept of informed buyers is operationalized by automated additional sales. The seller with the lowest price in a market will make two such additional sales at his/her posted price. In case of a tie, the sellers make one additional sale each. The additional sales do not affect buyers' payoffs.

After each game, sellers and buyers receive feedback on prices set in their market and on their own ECU earned. Buyers are never informed whether the price is set exogenously or by the sellers. After a game is completed, subjects are randomly re-matched into a new market. Matching is done within matching blocks of 8 subjects. In our analysis, we regard average behaviour within blocks as independent observations.

4.2 Hypotheses

Our main treatment measures are sellers' posted prices and buyers' search decisions in games where the price is not set exogenously. Given our chosen parameters, the no-search equilibrium exists and is unique. Consequently, the model predicts that there is no search in all treatments. As a result, theoretical price distributions, and therefore expected prices, are the same across treatments $T10$, $T20$ and $T30$, see Figure 1 and Table 1.

the probability of exogenous pricing. Note that the valuation (and price range) of 100 is not binding for our chosen parameters, and increasing this number would not change any equilibrium predictions. See e.g. [Hong and Shum \(2006\)](#) for estimation of search cost using field data.

¹³We automate purchases to zoom in on the key decision of buyers and to avoid ordering effects in the sampling of prices.

Figure 1: Theoretical price distributions by treatment

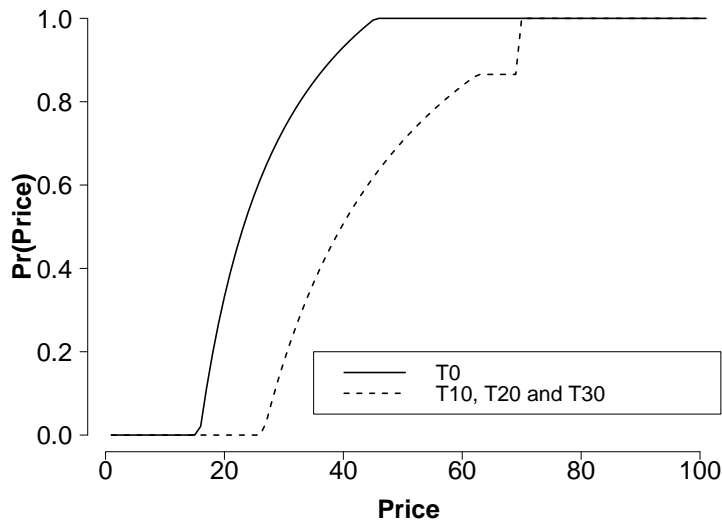


Table 1: Theoretical predictions

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

Based on the theoretical predictions, our primary hypothesis is that endogenous prices will be higher in the treatments with possible collusion than in the treatment without possible collusion. 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 Bayes' law.¹⁴

¹⁴See for instance [Tversky and Kahneman \(1971\)](#), [Kahneman and Tversky \(1972\)](#), [Ouwersloot et al. \(1998\)](#), [Charness and Levin \(2005\)](#), and [Alós-Ferrer and Garagnani \(2023\)](#)

Thus, there are reasons to believe that search decisions – and consequently rational price posting – may depend on the exogenous collusion probability in ways that differ from the model’s predictions.

A pre-study plan, including a pilot study for the experiment, was posted on the AEA RCT registry in May 2025.¹⁵ 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 significance level and a Wilcoxon rank sum test.

4.3 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.¹⁶ Subjects were never exposed to more than one treatment (between-subject design). Recruitment and subject 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). Sample instructions are provided in Appendix G. 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.¹⁷ 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.

¹⁵See <https://www.socialscienceregistry.org/trials/11401>.

¹⁶We argue that behaviour in our sample is representative for decision makers in market contexts. Mounting evidence shows that behaviour in convenience samples (CSs) is 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 Fréchet (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.

¹⁷A buyer’s payoff in a game is negative in the case he/she searches while both sellers charge a price equal to 100.

5 Experimental results

All the results presented exclude data from the first 20 games of each treatment.¹⁸ Furthermore, we exclude prices from games in which the price was set exogenously.

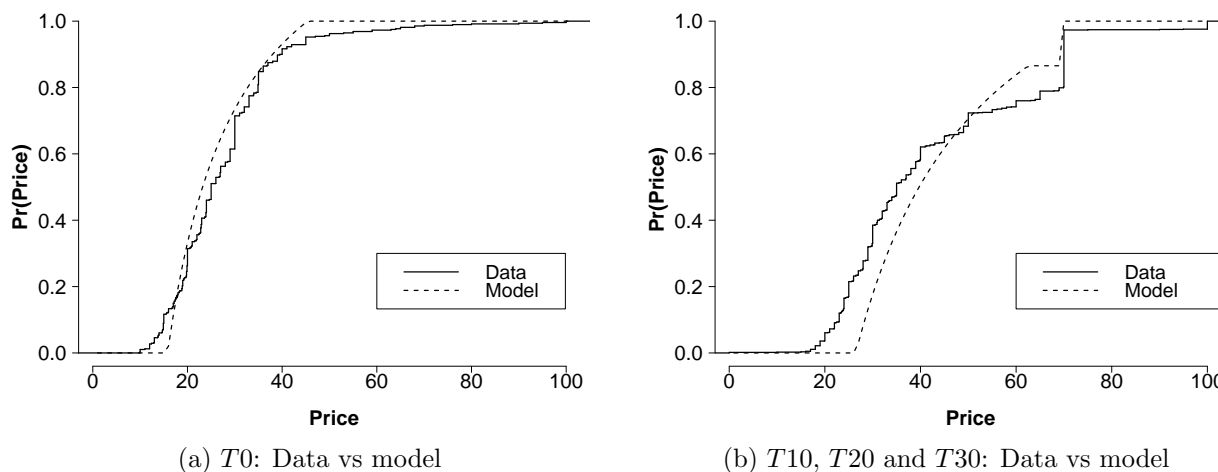
We start by comparing aggregate results from treatments with possible collusion (treatments $T10$, $T20$ and $T30$) with the treatment without possible collusion (treatment $T0$). In treatments with possible collusion ($x > 0$), prices posted by subjects are significantly higher than in treatment without possible collusion; see Table 2. In particular, posted prices in treatments with possible collusion 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.

Table 2: Regression

	Posted Price
<i>constant</i>	27.62*** (2.85)
$I\{x > 0\}$	14.85*** (4.19)
N	1960

Note: First 20 games and games where the price was set exogenously are excluded. Standard errors (in parentheses) are clustered at the matching group level.

Figure 2: Price distribution, theoretical predictions and data.



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

Next, consider the distribution of posted prices in Figure 2. We first note that the

¹⁸This data selection procedure is in accordance with our pre-study plan. Including the first 20 games does not impact our main results; see Appendix D.

empirical distributions are close to the theoretical distributions. In addition, Figure 2 reveals that the difference in average prices between treatment $T0$ and treatments $T10$, $T20$ and $T30$ is, as predicted by the model, partly driven by sellers posting prices at the level of the collusive price (70 ECU) in treatments $T10$, $T20$ and $T30$. The share of posted prices at 70 ECU in treatments $T10$, $T20$ and $T30$ is 0.17, while the share of posted prices at 70 ECU in treatment $T0$ is 0.002. Furthermore, the difference in average prices is also in part driven by sellers on average posting higher prices in the range below 70 ECU, as predicted by theory. Conditioning on the price being strictly below 70 ECU, the average price in $T0$ is 26.7 ECU while the average price in treatments $T10$, $T20$ and $T30$ is 34.7 ECU.

We divide the presentation of our remaining results into four subsections: Section 5.1 presents the empirical price distributions, average prices, and a comparison with equilibrium prices. Section 5.2 presents results on search behaviour and a comparison with equilibrium search behaviour. In Section 5.3 we analyse the optimal search behaviour of buyers given the empirical price distribution. In Section 5.4 we calculate the optimal pricing strategy of sellers given the observed search behaviour of buyers. Section 5.5 accounts for differences between treatment $T10$, $T20$ and $T30$ using a model of reinforcement learning.

5.1 Prices

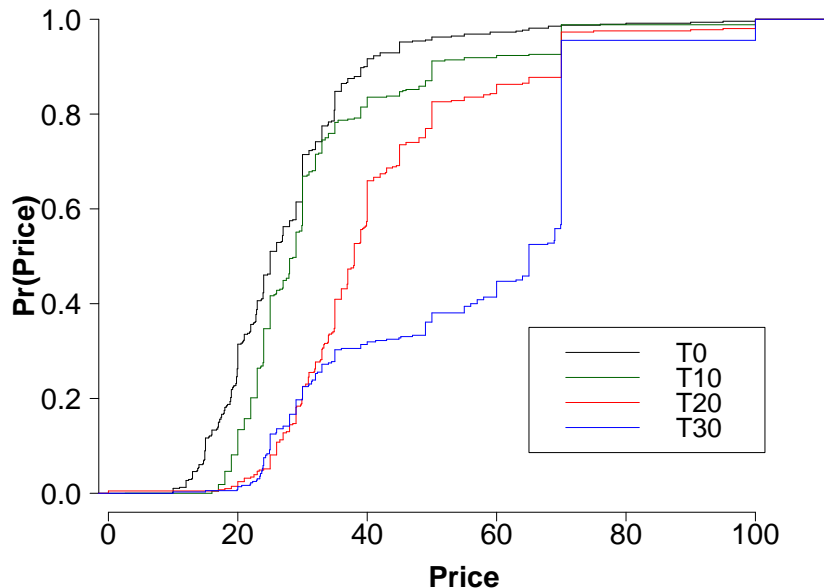
Figure 3 presents the empirical distribution of posted prices in the four treatments. Consistent with equilibrium predictions, the price distributions in treatments with possible collusion first-order dominate the distribution observed in the treatment without possible collusion. The shift in the distribution not only reflects that some sellers post a price of 70, but also that sellers who do not post 70 also post higher prices. That is, if we condition the empirical price distributions on posted prices being less than 70 ECU, we still find that the price distributions from treatments $T10$, $T20$ and $T30$ first order dominate the price distribution from the treatment $T0$.¹⁹

We also find that, consistent with the theoretical predictions, the price distributions in

¹⁹Kolmogorov-Smirnov tests for differences in distribution between $T0$ and the other treatments confirm that the price distributions in treatments $T10$, $T20$ and $T30$ are statistically different from the price distribution in $T0$. All tests produce p -values below 0.001, see Appendix D. The results are the same when we exclude price observations of 70 ECU or higher.

treatments $T10$, $T20$ and $T30$ all have a mass point at 70. The shares of posted prices exactly at 70 ECU in $T10$, $T20$ and $T30$, respectively, are 0.06, 0.1, and 0.39.²⁰ The share of posted prices exactly at 70 ECU in $T0$, by comparison, is only 0.002. The differences in shares of posted prices at 70 ECU between $T0$ and the remaining treatments are all statistically significant.²¹

Figure 3: Price distribution by treatment



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

Figure 4 shows the average prices posted 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 for 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, while the difference between $T0$ and $T10$ is not.²² We also note that average prices are significantly different across treatments $T10$,

²⁰Note that these shares are all statistically different from 0 ($T10$: $p = 0.034$; $T20$: $p = 0.031$; $T30$: $p = 0.031$), and that none of them are statistically different from the hypothesized share of 0.13 ($T10$: $p = 0.396$; $T20$: $p = 0.563$; $T30$: $p = 0.063$).

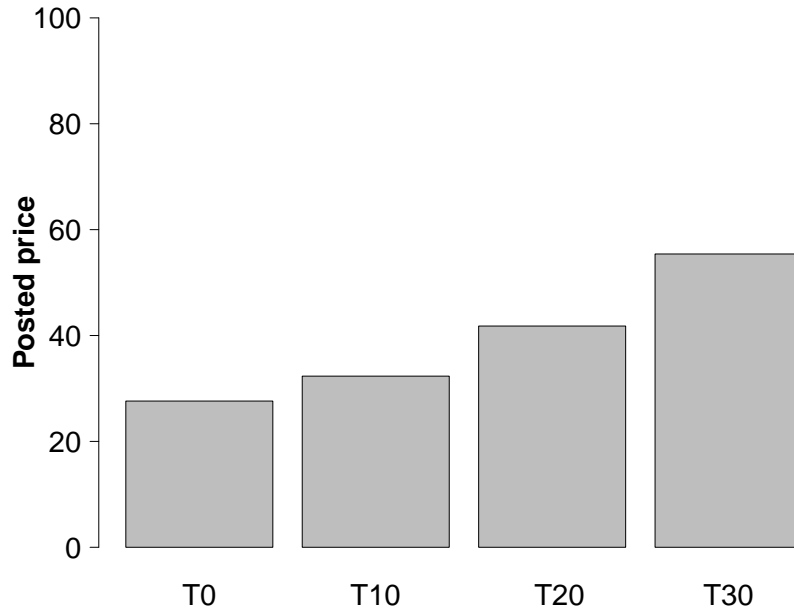
²¹Wilcoxon rank-sum tests result in the following p -values: $T0$ vs. $T10$: $p = 0.003$; $T0$ vs. $T20$: $p = 0.004$; $T0$ vs. $T30$: $p = 0.004$

²²Wilcoxon rank-sum tests result in the following p -values: $T0$ vs. $T10$: $p = 0.394$; $T0$ vs. $T20$: $p = 0.009$;

$T20$ and $T30$, with the exception of $T20$ vs. $T30$.²³

We interpret these results as broadly supportive of our main theoretical prediction: sellers set higher prices when sellers are uncertain about whether collusion is going on compared to when collusion cannot happen. However, the extent of these higher prices seems to depend on the size of the probability of collusion. In particular, while prices in treatments $T0$ and $T20$ are remarkably close to equilibrium, prices in $T10$ are lower than predicted, and prices in $T30$ are higher than predicted.

Figure 4: Average price by treatment



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

Focusing on equilibrium play, Tables 3 and 4 present the share of prices posted within different ranges. Considering the first treatment $T0$, we note that 86% of the prices fall within the support of the equilibrium price distribution ($[14.8, 44.4]$). For the remaining treatments, most of the prices also fall within the equilibrium range ($[26.5, 62.6] \cup 70$). The respective shares of prices within the equilibrium range in treatments $T10$, $T20$, and $T30$ are 55%, 85%, and 70%.

$T0$ vs. $T30$: $p = 0.004$

²³See Table 18 in Appendix D for a table of all treatment-by-treatment comparisons tests.

Table 3: Share of prices in different ranges in treatment $T0$

Treatment	$p \in [0, 14.8)$	$p \in [14.8, 44.4]$	$p \in (44.4, 100]$
$T0$	0.07	0.86	0.07

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

Table 4: Share of prices 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 where the price was set exogenously are excluded.

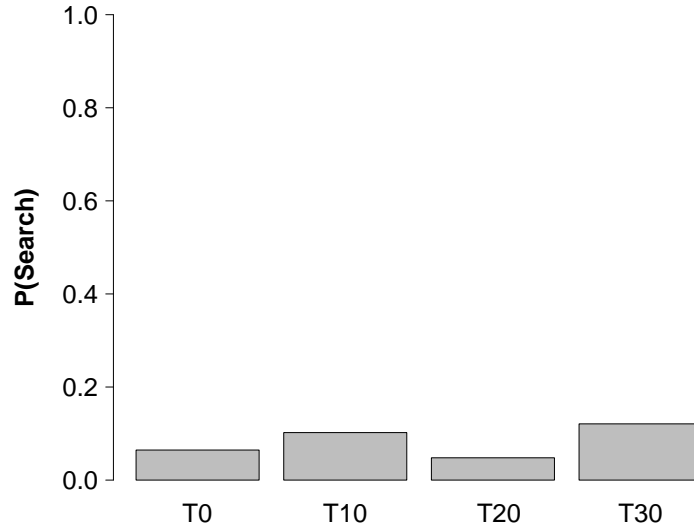
In treatment $T30$, a substantial share of prices fall within the out-of-equilibrium range $p \in (62.6, 70)$. This behaviour can be explained by the higher-than-equilibrium share of prices at 70. This gives sellers incentives to slightly undercut the price of 70 in order to sell to both informed buyers and searching uninformed buyers when the opponent sets 70, see Proposition 1. In section 5.4 we study best responses, and from Figure 6 it follows that setting a price just below 70 is actually a best response to the other players behaviour (including the buyers' search behaviour) in the $T30$ treatment.

5.2 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. Differences in search behaviour between treatments are not statistically significant.²⁴

²⁴See Table 20 in Appendix D.

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 prices below the support of the equilibrium prices. For the remaining price ranges, search decisions deviate from equilibrium predictions in some cases. In treatment $T0$, buyers search too little for off-path prices: Only a share of 0.65 decide to search when observing a price in excess of the upper bound of the equilibrium price distribution. In treatment $T10$, a relatively high share (0.28) of the buyers search following a price of 70 ECU. Moreover, a higher share search when observing a price in the equilibrium range $p \in [26.5, 62.6]$, compared to the other treatments. This behaviour is complemented by a large number of prices posted below the equilibrium range.

In treatment $T20$, search mainly takes place after having observed a price of 70 ECU, though arguably with a low share. In treatment $T30$, however, this share is larger, and is, in combination with the large number of prices at 70 ECU, the main driver for the relatively large search rate observed in Figure 5 for this treatment.

Table 5: Search by price range in treatment $T0$

Treatment	$p \in [0, 14.8)$	$p \in [14.8, 44.4]$	$p \in (44.4, 100]$
$T0$	0.0 (33)	0.02 (413)	0.65 (34)

Note: First 20 games are excluded. Number of posted prices in price range in parentheses.

Table 6: Search by price range 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 (185)	0.1 (214)	1 (1)	0.28 (27)	1 (5)
$T20$	0 (44)	0.01 (308)	0.33 (6)	0.08 (39)	1 (11)
$T30$	0 (49)	0.03 (112)	0.12 (43)	0.14 (140)	0.94 (16)

Note: First 20 games are excluded. Number of posted prices in price range in parentheses.

5.3 Implied reservation prices and optimal search behaviour

Given the empirical price distributions, we calculate the implied reservation prices and the optimal search behaviour of the buyers in each treatment. We then compare the optimal search behaviour to the actual search behaviour in each treatment to determine the degree to which buyers in our experiment best respond.

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 $T30$ we also need to take into account that a buyer's posterior belief depends on whether the observed price is exactly 70 or not. For a price of 70, we compute the posterior beliefs that the price has been set exogenously by using the observed frequencies of prices posted at 70 ECU when sellers set prices freely. The implied reservation prices are presented in Table 7.

Table 7: Reservation prices implied by the empirical price distributions

Treatment	Implied reservation price
$T0$	47.6
$T10$	52.3/76.4
$T20$	61.8/79.8
$T30$	75.4/84.7

Note: First 20 games are excluded. For treatments $T10$, $T20$ and $T30$ the first number is the implied reservation price after observing a price different from 70 ECU and the second number is the implied reservation price given the updated posterior beliefs when observing a price of 70 ECU.

If buyers in our experiment are best responding, given the empirical distribution of prices, they would always search whenever the price is in excess of the implied reservation prices in Table 7, and never search when the price is below implied reservation prices in Table 7. Comparing this optimal search behaviour with the actual search behaviour in Table 8 we note that the overall pattern is remarkably consistent with the best responses of buyers. In

particular, across all treatments more than 90 percent of the decisions made by buyers are consistent with a best response.

Table 8: Shares who search for prices at or below and above reservation price

Treatment	Observed price at or below implied reservation price	Observed price above implied reservation price	Overall share who best respond
<i>T0</i>	0.02	0.9	0.97
<i>T10</i>	0.08	1	0.92
<i>T20</i>	0.02	0.76	0.97
<i>T30</i>	0.09	0.94	0.91

Note: First 20 games are excluded.

5.4 Profits and optimal pricing strategy

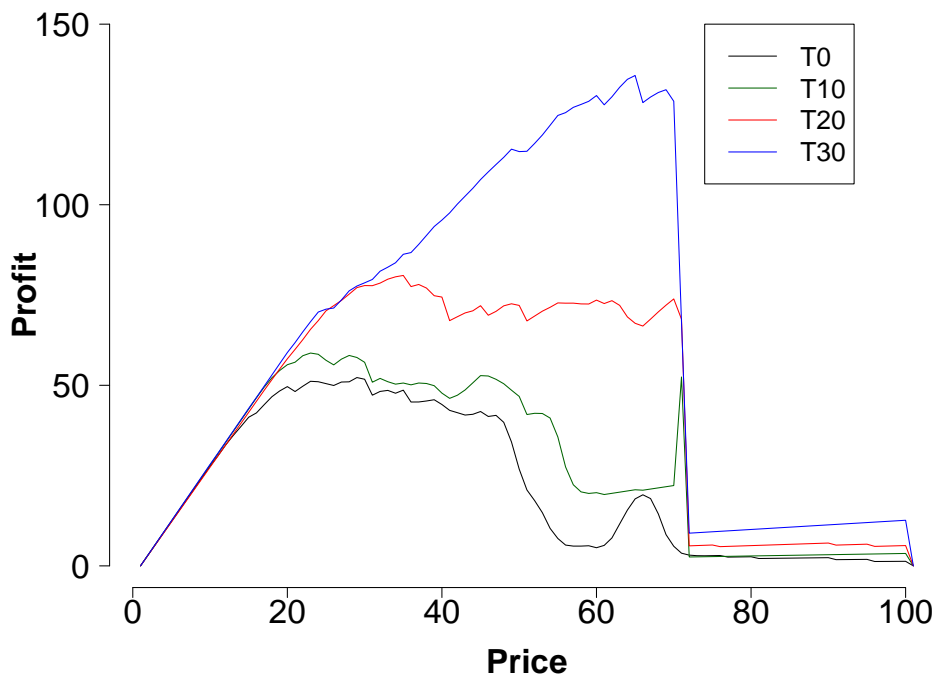
The analysis in the previous subsection shows that buyers, to a large degree, best respond given the empirical distribution of prices. In this subsection, we examine whether sellers make optimal decisions based on the search patterns of buyers and the pricing strategies of other sellers. To do so, we estimate expected profits as a function of posted prices using the empirical price distribution and estimates of search propensities.²⁵ Estimated profits for all four treatments are presented in Figure 6.

Figure 6 shows that in treatments *T0*, *T10* and *T20* expected profits are of the same magnitude for a range of prices, in line with the mixed equilibrium prediction of the model. For treatment *T30*, expected profits are more single-peaked. Given these expected profits, 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 behaviour in the laboratory is profit-maximizing. Therefore, we define what we call a *reasonable best response* as a price that in expectations yields a payoff of at least 75, 80 or 85 percent of the highest expected payoff within a treatment. For the 75 percent cut, this implies that any price that in expectations results in a payoff of at least 39.1, 44.2, 60.3, and 101.8 in treatments *T0*, *T10*, *T20* and *T30*, respectively, constitutes a reasonable best

²⁵For treatment *T0*, search propensities for the entire price range are estimated using a Gaussian kernel smoother with a bin width of 5. For treatments *T10*, *T20* and *T30*, search propensities for prices in the range $[0, 70)$ are estimated using a Gaussian kernel smoother with a bin width of 5; for prices posted at 70 ECU, the search propensity is set to equal to the rates in Table 6; for prices above 70 ECU, the search propensity is set to 1.

response. Table 9 reports the share of posted prices that are within the range of a reasonable best response in the four treatments. For all our definitions of a reasonable best response, a majority of posted prices fall within the implied ranges of prices.²⁶

Figure 6: Expected profit by price and treatment



Note: Profit is calculated using the empirical price distribution from the last 20 rounds, excluding rounds where price is set exogenously, along with estimated search propensities.

Table 9: Share of posted prices within the range of a reasonable best response across treatments and for three definitions of a reasonable best response

Definition of <i>reasonable best response</i>	T0	T10	T20	T30
$\geq 75\%$	0.91	0.93	0.95	0.63
$\geq 80\%$	0.87	0.90	0.94	0.62
$\geq 85\%$	0.78	0.86	0.66	0.58

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

²⁶In Appendix F we document heterogeneity in subjects' average price posting as well as their propensity to post a price of 70 ECU.

5.5 Accounting for differences between $T10$, $T20$ and $T30$

The theoretical model accounts for important features of the data, but there are inconsistencies. Most notably, the share of posted prices at 70 ECU seems to be related to the exogenous probability at which this price is posted. This may suggest that subjects' beliefs about how other subjects play differs across treatments, which in turn affects their own optimal strategy. To formalize this notion, we use the frequently-used reinforcement learning model developed by Roth and Erev (1995) and Erev and Roth (1998).²⁷

In the reinforcement learning model, it is assumed that each action is associated with an *attraction*. The attraction of a given action depends on the initial attraction and the historical payoffs associated with that action. The probability of a given action is determined in a logit structure with a sensitivity parameter λ and the attractions as weights.²⁸

The initial attraction is estimated together with the sensitivity parameter λ and a parameter reflecting the tendency to forget. When estimating the model, we assume that subjects cannot learn from rounds where the price is set exogenously. Estimates together with actual play can then be used to predict choices.

Table 10: Predicted fractions of prices in different ranges in the first game in treatments $T10$, $T20$ and $T30$

Treatment	$p \in [0, 26.5)$	$p \in [26.5, 62.6]$	$p \in (62.6, 70)$	$p = 70$	$p \in (70, 100]$
$T10$	0.17	0.54	0.05	0.19	0.05
$T20$	0.04	0.70	0.03	0.20	0.03
$T30$	0.04	0.28	0.07	0.58	0.03

Note: Games where price is set excluded are excluded.

We focus first on the initial attraction related to posting a price of 70 ECU and how this varies across treatments. Given these initial attractions, we can estimate the likelihood of posting prices within different ranges in the first game. As indicated by the probabilities in Table 10, the initial attractions for different ranges differ between treatments. This finding suggests that the variation in play across treatments can be rationalized by the subjects' initial beliefs about the optimal strategy depend on the probability of collusion. Furthermore,

²⁷See Masiliūnas (2023) for a recent overview of payoff learning models. Feltovich (2000) and Charness and Levin (2005) contrast Bayesian updating with (reinforcement) learning. See also Alós-Ferrer and Garagnani (2023) for an overview of this literature on Bayes vs. learning.

²⁸See Appendix E for details.

throughout the 40 games, these initial differences in beliefs across treatments persist as they affect what subjects learn during play.

Table 11: Predicted fractions of prices in different ranges in the last 20 games in treatments $T10$, $T20$ and $T30$

Treatment	$p \in [0, 26.5)$	$p \in [26.5, 62.6]$	$p \in (62.6, 70)$	$p = 70$	$p \in (70, 100]$
$T10$	0.31	0.51	0.04	0.09	0.05
$T20$	0.06	0.77	0.04	0.09	0.04
$T30$	0.11	0.33	0.14	0.36	0.06

Note: Games where price is set excluded are excluded.

Next, we will examine how the learning model can account for subjects' price posting in the last 20 games. Comparing predictions of the learning model in Table 11 to the empirical results in Table 4 and the theoretical predictions in Table 1, we note that the learning model can account for patterns in the data that cannot be explained by the theoretical model. The learning model reproduces the observed high share of posted prices at 70 in treatment $T30$ compared to $T10$ and $T20$. Furthermore, the learning model reproduces prices below the equilibrium range, $[0, 26.5)$, as we do observe in the data in all the treatments. In the learning model, the share of prices below the equilibrium range is notably higher in the $T10$ than in the other treatments, which is also consistent with the data.

6 Discussion

In this section, we first discuss generalizations of our theoretical results. We allow for a stochastic collusion price, and then for more than two sellers. Next, we explore the effects of possible collusion in the [Burdett and Judd \(1983\)](#) framework. Finally, we discuss some policy implications of our findings.

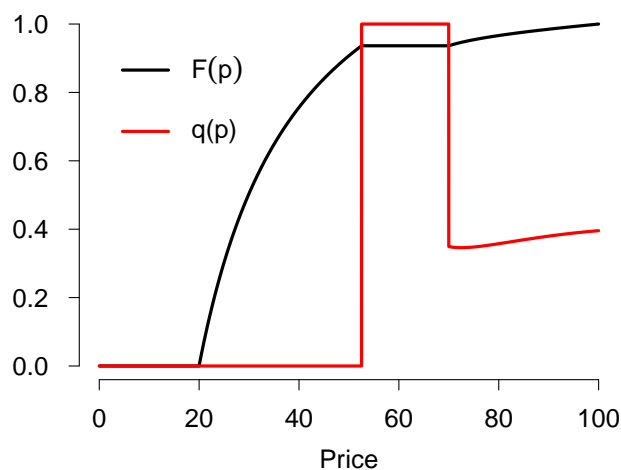
6.1 Stochastic collusion price

In the main model we assume that with probability x sellers collude on price p^M . Here we maintain the assumption that firms collude with probability x . However, conditional on collusion, we assume that the collusion price is stochastic with distribution $G(p)$, where $G(p)$

is continuous with support $[p^M, 100]$. When there is no collusion, equilibrium prices will be continuously distributed over two ranges.²⁹ Unlike in our baseline model there is no mass point at p^M , instead there will be a distribution over prices in the range $p \geq p^M$.

In Figure 7 we present the equilibrium price distribution, $F(p)$, and search probabilities, $q(p)$, for parameters as used in the experiment when the stochastic collusion price is given by a uniform distribution on $[70, 100]$.³⁰ We see that no sellers set prices in the interval $[52.54, 70)$. Importantly, the key insights from the baseline model are robust to a stochastic collusion price. First, sellers set prices consistent with collusion. Second, the distribution below the collusion prices shifts upwards compared with the Stahl distribution.

Figure 7: Price distribution and search probabilities with stochastic collusion price



Note: Equilibrium for $c = 20$ and $x = 0.2$. The collusion price is uniformly distributed on $[70, 100]$.

6.2 Many sellers

Multiple sellers ($n > 2$) will not change the equilibrium structure.³¹ That is, in equilibrium when $n > 2$, sellers mix between setting the collusion price and prices in some interval $[p_0, p_1]$. Furthermore, depending on parameters, equilibrium may be with or without search as in the case with two sellers.

²⁹The analysis is located in Appendix B.

³⁰The numerical procedure for calculating the equilibrium is available upon request.

³¹Details are provided in Appendix B.

6.3 Possible collusion in the Burdett-Judd model

The focus of the paper is on the Stahl model of sequential search. The other leading model of consumer search is [Burdett and Judd \(1983\)](#). In a standard version of this model there is a large number of sellers, and buyers observe one or two prices and can then pay to observe an additional price. We argue that this model is isomorphic to the Stahl model with two sellers: Buyers who observe two prices in the Burdett-Judd model are the informed buyers in the Stahl model, buyers who observe one price in the Burdett-Judd model are the uninformed buyers in the Stahl model, and there is no search in equilibrium.³² Hence, the equilibrium characterization in [Proposition 1](#) is still valid, and the effect of possible collusion is the same as in the Stahl model.

Burdett and Judd also analyse non-sequential search. Buyers decide ex-ante how many price quotes to elicit, one or two. After observing the prices, buyers cannot search again. In this environment, possible collusion reduces the value of eliciting two price quotes, as the value of observing a second price will be zero if there is collusion. In the stable equilibrium buyers search less and prices will be higher, see equations 2 and 3 in [Burdett and Judd \(1983\)](#).

6.4 Policy implications

Our mechanism suggests that collusion may be even more detrimental to consumer welfare than previously believed. Not only does collusion inherently lead to higher prices when it occurs. Collusive behaviour in certain markets (at specific times) may provoke suspicion of collusion, resulting in increased prices in other markets and/or at different times. This belief channel may be affected by competition authorities' investigations into collusion.

Furthermore, our mechanism suggests that collusion may be harder to detect than it otherwise would be, as prices may be high due to fear of collusion even though collusion does not take place. It may therefore be challenging for the competition authorities to distinguish between actual collusion and competition with fear of collusion.

³²We need only set the measure of buyers per seller equal to $u + \frac{I}{2}$ and the share of buyers who observe one price equal to $\frac{u}{u + \frac{I}{2}}$ and the share who observe two prices, denoted q_2 , equal to $\frac{\frac{I}{2}}{u + \frac{I}{2}}$.

7 Conclusion

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

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Appendix

The Appendix contains the following sections:

- A. Proofs
- B. Model extensions
- C. Simulations
- D. Results
- E. Learning model
- F. Heterogeneity
- G. Sample instructions

A Proofs

A.1 Proof of Proposition 1

We first show that equilibrium must have the structure described in Proposition 1. We then prove existence.

Equilibrium structure: In equilibrium (if it exists), a positive mass of sellers posts p^M . If not, all buyers know that collusion does not take place, and the model is isomorphic to the Staahl model, which has a unique equilibrium. But, as shown in the main text, the Stahl equilibrium cannot be an equilibrium as sellers will have an incentive to deviate and post p^M . Hence, there must exist a mass point at p^M .

The mass point at p^M has mass less than 1. If not, a deviating seller setting p^{M-} would attract all informed buyers in addition to its share of uninformed buyers who would not search (as there are no cheaper sellers around). Hence, the deviation is profitable, and we cannot be in equilibrium.

Let p_0 denote the infimum of the support of the equilibrium distribution F . Since search is costly, buyers do not search if the price is sufficiently close to p_0 . Define $p_1 \leq 1$ as the

solution to $p_1 - E^{p'} \min[p_1, p'] = c$ ($\leq c$ if $p_1 = 1$) conditional on no collusion taking place. Clearly, p_1 (for a given F) is unique. Note that for all $p \neq p^M$, an uninformed buyer searches with probability 0 if $p \leq p_1$ and with probability 1 if $p > p_1$.

It follows that $p_1 < p^M$. Suppose not. Then there exists a price p^{M-} arbitrarily close to p^M such that a seller setting p^{M-} will attract all informed buyers whenever the opponent plays p^M , and will sell to at least equally many uninformed buyers as at p^M . Hence, the profit must be strictly higher at p^{M-} than at p^M , which is not consistent with equilibrium.

From the standard [Varian \(1980\)](#) argument, it follows that $F(p)$ is continuous with no holes below p_1 .

There is an interval above p_1 that is not in the support of F , as it is more profitable to set p_1 than setting p' just above p_1 , at which uninformed buyers search with probability 1. It follows that the interval $[p_2, p^M)$, if it exists, must satisfy $p_2 > p_1$ (otherwise it cannot be connected), and buyers will search at all the prices in the interval. The supremum of this interval must be p^M , if not a seller at the top of the interval would find it profitable to deviate and set a price just below p^M .

Suppose that there is an interval of prices $[p_4, p_5]$ strictly above p^M . As just shown, buyers visiting these sellers will search. Therefore, the seller setting p_5 will not have any sales and hence will not make any profit, which is inconsistent with equilibrium. Therefore, such an interval cannot exist.

Proof of existence: We first specify the model in the general case. To this end, we relabel ρ, ρ_b, ρ_s to ρ_0, ρ_1, ρ_2 . Let F^b denote the distribution on $[p_2, p^M)$ when $\rho_1 > 0$.

Consider the gain from search at p^M . The probability that collusion does not occur is x^M . Given that collusion does not occur and the opponent sets a price in the lower interval $[p_0, p_1]$, the gain from search is $c + p^M - p_1$. If the opponent sets a price in the $[p_2, p^M]$ interval, the gain from search is $\int_{p_2}^{p^M} F^b(p) dp$. The gain from search, which we denote κ must be less than or equal to the cost of search c . It follows that

$$\kappa = (1 - x^M) \left[c + \rho_2 [p^M - p_1] + \rho_1 \int_{p_2}^{p^M} F^b(p) dp \right] \leq c \quad (11)$$

In the general case, the equilibrium of the model is a vector of probabilities $[\rho_0, \rho_1, \rho_2]$ which

sums to 1, a price p_1 , a continuous distribution F^b with supremum of support equal to p^M , a continuous distribution F with supremum of support given by p_1 , a probability q , and a profit level π such that

1. Profit at p^M is equal to π :

$$p^M [u(1 - q) + \rho_0(uq + I/2)] = \pi \quad (12)$$

2. At p^M , the expected gain from search is less than or equal to c and equal to c whenever $q > 0$; $q \cdot (\kappa - c) = 0$ (complementary slackness).

3. If $\rho_1 > 0$, then any p in support $[p_2, p^M)$ of F^b gives profits π :

$$p [\rho_0(I + (1 + q)u) + \rho_1(1 - F^b(p))(I + 2u)] = \pi \quad (13)$$

and p_2 is defined so that $F^b(p_2) = 0$.

4. For any p in the support $[p_0, p_1]$, profit is equal to π , that is,

$$p [(1 - F(p)\rho_2)I + (1 + \rho_0q + \rho_1)u] = \pi \quad (14)$$

5. At p_1 , the buyer is indifferent between searching and not searching

$$\rho_2 \int_{p_0}^{p_1} F(p)dp = c \quad (15)$$

while p_0 is determined such that $F(p_0) = 0$.

Consider the vector $\mathbf{z} = [\rho_i, q, p_1] \in [0, 1]^5$, $i \in \{0, 1, 2\}$, with $\rho_i, q \in [0, 1]$ and $p_1 \in [c, p^M]$. We want to construct a continuous mapping $\mathbf{z}' = \Gamma(\mathbf{z})$ such that a fixed point of the mapping satisfies the equilibrium requirements for $[\rho_i, q, p_1]$

Let \mathbf{z} be given. Define π_0 as the profit at p^M defined by the left-hand side of (12). Define π_1 as the profit defined by the left-hand side of (13) evaluated at $p = p^M$. Define π_2 as the profit defined by the left-hand side of (14) evaluated at p_1 . Clearly π_i is continuous in \mathbf{z} .

Given \mathbf{z} , π_1 and π_2 , (13) with $\pi = \pi_1$ defines $F_b(p)$, and (14) with $\pi = \pi_2$ defines $F(p)$. Then the left-hand side of (11) defines κ . The left-hand side of (15), which we denote κ_{p_1} , defines the value of search at p_1 . Again, it follows immediately that κ and κ_{p_1} are continuous in \mathbf{z} .

We update ρ_i as follows. First define

$$\hat{\rho}_i = \max\left[\rho_i + \frac{\pi^i}{\sum_i \pi_i} - \frac{1}{3}, 0\right]$$

Since $\pi_2 \geq uc$ the expression is well defined, and since $\sum_i \rho_i = 1$ we have that $\sum_i \hat{\rho}_i \geq 1$. Then define the updated values of ρ as

$$\rho'_i = \frac{\hat{\rho}_i}{\sum_i \hat{\rho}_i} \tag{16}$$

We define $\hat{q} = q + \kappa/c - 1$, and let $q' = \min[\max[\hat{q}, 0], 1]$. Define $\hat{p}_1 = p_1 \kappa_{p_1}/c$, and let $p'_1 = \max[c, \min[\hat{p}_1, p^M]]$

Let $\mathbf{z}' = [\rho'_i, q', p'_1]$. Then we have constructed a mapping $\mathbf{z}' = \Gamma(\mathbf{z})$ from a closed and bounded set onto itself that is continuous. Hence, Brouwer's fixed-point theorem guarantees that the mapping has a fixed-point \mathbf{z}^* which solves $\mathbf{z}^* = \Gamma(\mathbf{z}^*)$.

Furthermore, these values of \mathbf{z}^* by definition ensure that the profit is equal at p^M , p_1 . By construction we must have $\kappa_{p_1} = c$ and $(\kappa - c)q = 0$.

We only have to show that the bounds we have imposed on p_1 do not bind. Suppose $p_1 = c$. We have to show that $\kappa_{p_1} \leq c$ at $p_1 = c$. But this follows from the fact that prices are bounded below by 0. Suppose then that $p_1 = p^M$. If $\rho_0 > 0$, it follows that $\pi_2 > \pi_0$, since sellers at p_1 attract the informed buyers when the opponent plays p^M . If $\rho = 0$, it follows by assumption ($p_S < p^M$) that buyers strictly want to search at $p_1 = p^M$, which is inconsistent with being at the fixed-point.

Finally, we want to show that $q < 1$. Suppose not. Since $\rho_0 > 0$, it then follows that the profit defined by (13) is strictly less than the profit defined by (14) evaluated at p^M , a contradiction.

A.2 Proof of symmetry

We want to show that the equilibrium is symmetric. Suppose it is not, and denote the distributions of the two sellers by G^1 and G^2 . Buyers do not know which of the sellers they meet, but update according to Bayes rule. It follows that the search decision of buyers for a given p is the same for the two sellers.

Due to the standard undercutting argument, both agents play with mixed strategies. Let p_0^i be the infimum of the price of seller i . Then $p_0^1 = p_0^2 (= p_0)$, otherwise the seller with the lowest cost would increase his price. Since search is costly, there must be an area above p_0 without search. Let p_1 be the highest price with no search. Standard arguments imply that the distributions are continuous with no wholes in this interval. The profit at p_0 for player i is

$$\pi_i = p_0(I + z^{-i}) \quad (17)$$

where z^{-i} is the mass of searching uninformed buyers first visiting seller i , which depends on the opponent's price distribution (hence $-i$). We assume that $z^2 > z^1$. Then $\pi_1 > \pi_2$. The profit at $p_1 > p_0$ reads

$$\pi_i = p_1(I(1 - \rho_2^{-i}) + z^{-i}) \quad (18)$$

where ρ_2^{-i} is the probability that seller $-i$ sets the price at or below p_1 . Equal profit at p_1 and p_0 implies that since $z^2 > z^1$, then $\rho_2^2 > \rho_2^1$.

Since G_2 has more mass at low p than G_1 , buyers may not search at higher prices than p_1 if they know that player 2 sets the price. Hence there may exist a mass point at price $\tilde{p}_1 > p_1$ at which seller 2 sets the price, and buyers search with probability $\tilde{q} < 1$ such that seller 2 is indifferent between p_1 and \tilde{p}_1 . Denote the mass at this point by \tilde{p} .

However, for player 1, the only possibility is to set a price in $p_1 \in (p_1, p^M)$ at which the buyers search with probability 1, or at p^M .

Suppose seller 1 sets the rest of the mass, $1 - \rho_2^1$, in (p_1, p^M) . Since $\rho_2^1 < \rho_2^2$, it follows that $z^1 > z^2$, a contradiction.

Suppose then that seller 1 also sets part of the mass at p^M . Since seller 1 has strictly

higher profit than seller 2, it follows that $\rho_0^2 > \rho_0^1$. But then both $\rho_0^1 < \rho_0^2$ and $\rho_2^1 < \rho_2^2$. Hence,

$$\begin{aligned}
z^1 &= 1 - \rho_2^1 - (1 - q)\rho_0^1 \\
&> 1 - \rho_2^2 - (1 - q)\rho_0^2 \\
&\geq 1 - \rho_2^2 - (1 - q)\rho_0^2 - (1 - \tilde{q})\tilde{\rho} \\
&= z^2
\end{aligned} \tag{19}$$

a contradiction.

Suppose then that $z^1 = z^2$. Then profits at p_0 and hence overall are the same. Hence $\rho_i^1 = \rho_i^2$, for $i = 0, 1, 2$. At p_1 (and above) the incentives to search are the same, independently of posteriors over type. It follows that the equilibrium has to be symmetric.

A.3 Proof of Proposition 2

As above, we relabel ρ to ρ_0 for internal consistency in the Appendix. For any given ρ_0 , the continuous part of the model, equations (3) and (4), is isomorphic to the Stahl model with $u' = \tilde{u}$, $I' = \tilde{I}$, and $c' = c/(1 - \rho_0)$, and it follows easily that F and $[p_0, p_1]$ exist and are unique. Let $p_1(\rho_0)$ denote the corresponding value of p_1 . It follows that $p_1(\rho_0)$ is continuous in ρ_0 .

As in the previous proof, we write the profits π_0 and π_2 at p^M and p_1 , respectively, as functions of ρ_0 . Since by assumption $\rho_1 = 0$, we simply write $\pi_0 = \pi_0(\rho_0)$ (defined by (12)) and $\pi_2 = \pi_2(\rho_0)$ (defined by (14)). Both are continuous in ρ_0 . Hence, to show existence, it is sufficient to show that $\pi_2(0) < \pi_0(0)$ and that $\pi_2(\rho_0) > \pi_0(\rho_0)$ for some $\rho_0 > 0$.

For $\rho_0 = 0$, sales at p^M are the same as at p_1 , hence $\pi_0(0) > \pi_2(0)$. For high values of ρ_0 , $p_1 = 1$. Hence, there exists a lowest value $\bar{\rho}_0 \in (0, 1)$ such that $p_1(\rho_0) = p^M$. For p_1 sufficiently close to p^M , $\pi_2(\rho_0) > \pi_0(\rho_0)$, since the sales at p_1 are $I\rho_0/2$ higher than at p^M . It follows that for ρ_0 sufficiently close to $\bar{\rho}_0$, $\pi_2(\rho_0) > \pi_0(\rho_0)$. Hence, there must exist a value of $\rho_0 < \bar{\rho}_0$, which we denote ρ_0^* , such that $\pi_2(\rho_0^*) = \pi_0(\rho_0^*)$. This completes the proof of

existence.

Uniqueness requires that equation $\pi_2(\rho_0) = \pi_0(\rho_0)$ has a unique solution. It is sufficient to show that, evaluated at ρ_0^* , $\pi_2(\rho_0) - \pi_0(\rho_0)$ is increasing in ρ_0 (then the curves cannot cross twice).

First note that at ρ_0^* , $\pi_0 = \pi_2$, and hence

$$(p_1 - p^M/2)\rho_0 I = u(p^M - p_1) > 0,$$

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

$$\frac{d}{d\rho_0}(\pi_2 - \pi_0) = (p_1 - p^M/2)I + \frac{dp_1}{d\rho_0}(\rho_0 I + u) > 0$$

evaluated at ρ_0^* , since $p_1 > p^M/2$ and $\frac{dp_1}{d\rho_0} > 0$.

A.4 Proof of proposition 4

We know that there are no other no-search equilibria. We therefore have to show that there does not exist any search equilibrium.

For any vector (ρ_0, ρ_2, q) , the rest of the equilibrium objects are well defined. π_0 (the profit at p^M) is defined by (12). π_1 (the profit at p^{M-}) is defined by (13) evaluated at p^M , and F_b is defined by the same equation. $F(p)$ and p_1 , and hence also π_2 are defined by (14) and (15). We write the profits in this "partial equilibrium" as $\pi_i(\rho_0, \rho_2, q)$, $i = 0, 1, 2$ (the restriction that $\sum_{i=0}^2 \rho_i = 1$ is built into the expressions). We define $\Delta(\rho_0, \rho_2, q) \equiv \pi_2(\rho_0, \rho_2, q) - \pi_0(\rho_0, \rho_2, q)$. The partial equilibrium value of search at p^M , $\kappa(\rho_0, \rho_2, q)$, is defined by (11). We denote the no-search equilibrium values of ρ_i by ρ_i^* .

From the proof of the uniqueness of the no-search equilibrium, we know that $\pi_2(\rho_0, 1 - \rho_0, 0) > \pi_0(\rho_0, 1 - \rho_0, 0)$ for $\rho_0 > \rho_0^*$ and that $\pi_2(\rho_0, 1 - \rho_0, 0) < \pi_0(\rho_0, 1 - \rho_0, 0)$ for $\rho_0 < \rho_0^*$. Hence $\Delta(\rho_0, 1 - \rho_0, 0)$ is strictly positive for $\rho_0 > \rho_0^*$ and strictly negative for $\rho_0 < \rho_0^*$ (property 1). We also have that $\pi_2(\rho_0, 1 - \rho_0, q)$ is strictly increasing in q , while $\pi_0(\rho_0, 1 - \rho_0, q)$ is strictly decreasing in q . Hence $\Delta(\rho_0, \rho_2, q)$ is strictly increasing in q (property 2).

We know that $\pi_2(\rho_0, \rho_2, q)$ is strictly decreasing in ρ_2 while $\pi_0(\rho_0, \rho_2, q)$ is independent of

ρ_2 (note that an increase in ρ_2 for a given ρ_0 implies an equal decrease in ρ_1). Reducing ρ_2 and increasing ρ_1 trivially leads to an increase in π_2). Hence $\Delta(\rho_0, \rho_2, q)$ strictly decreases in ρ_2 (property 3).

$\pi_2(\rho_0, \rho_2, q)$ strictly decreases in ρ_0 (since this means that ρ_s decreases with the same amount, and all buyers that meet a ρ_s -seller search, while only a fraction $q < 1$ of the buyers at p^M search). π_0 by contrast increases in ρ_0 . Hence $\Delta(\rho_0, \rho_2, q)$ strictly decreases in ρ_0 (property 4).

We have that $\kappa(\rho_0, \rho_2, q)$ is strictly decreasing in q (property 5). This follows from the fact that an increase in q shifts both F and F_b in (13) and (14) up, as it increases the number of effectively uninformed customers while the number of informed customers is unaffected.

Suppose that there is another equilibrium with search, and denote by $\hat{\rho}_i, \hat{q}$ the values of ρ_i and q in this equilibrium. Suppose first that $\hat{\rho}_0 \geq \rho_0^*$. Then we have

$$\begin{aligned} \Delta(\rho_0^*, 1 - \rho_0^*, 0) &\leq \Delta(\hat{\rho}_0, 1 - \hat{\rho}_0, 0) \\ &\leq \Delta(\hat{\rho}_0, 1 - \hat{\rho}_0, \hat{q}) \\ &\leq \Delta(\hat{\rho}_0, \hat{\rho}_2, \hat{q}) \end{aligned}$$

with at least one inequality being strict (otherwise $(\hat{\rho}_i, \hat{q}) = (\rho_i^*, 0)$). The first inequality comes from property 1, the second from property 2, and the third from property 3, as $\hat{\rho}_2 \leq 1 - \hat{\rho}_0$. Since $\Delta(\rho_0^*, 1 - \rho_0^*, 0) = 0$ this implies that $\pi_0(\hat{\rho}_0, \hat{\rho}_2, \hat{q}) < \pi_2(\hat{\rho}_0, \hat{\rho}_2, \hat{q})$, a contradiction.

Suppose then that in equilibrium with search, $\tilde{\rho}_0 < \rho_0^*$. Given Assumption 1 stated below, we know that there is no search at p^M for $\rho_0 < \rho_0^*$ and $q = \rho_1 = 0$.

Then in equilibrium, buyers do not search when $\rho_1 = q = 0$. We want to show that there cannot be an equilibrium in which there is search. From property 5 we know that $\kappa(\rho_i, q)$ is strictly decreasing in q , as p_1 and F_b shifts up.

A necessary condition for search if $q = 0$, and hence also for $q > 0$, is thus that $\hat{\rho}_1 + \hat{\rho}_2 > \rho_2^*$; there is no search at ρ_0 and $\rho_2 = 1 - \rho_0$ for $\rho_0 \leq \rho_0^*$, and increasing the mass at ρ_1 from zero at the expense of ρ_2 reduces the incentives to search at p^M . Hence we must have that

$$\begin{aligned}
\Delta(\rho_0^*, \rho_2^*, 0) &\leq \Delta(1 - \hat{\rho}_2, \hat{\rho}_2, 0) \\
&< \Delta(\hat{\rho}_0, \hat{\rho}_2, 0) \\
&\leq \Delta(\hat{\rho}_0, \hat{\rho}_2, q)
\end{aligned} \tag{20}$$

where the first inequality comes from property 1, the second from property 3 (since $\rho_1 > 0$), and the third from property 2. Again we have derived a contradiction, which completes the proof.

Derivation of assumption 1. We need an explicit expression for p_1 given that $\rho_1 = 0$ and $q = 0$. From (14) we have $1 - F(p) = \frac{p_1 - p}{p}k$, where $k = \frac{u + \rho I}{(1 - \rho)I}$. It follows that $p_0 = \frac{k}{1 + k}$.

We know that p_1 satisfies $(1 - \rho) \int_{p_0}^{p_1} F(p) dp = c$ Now

$$\begin{aligned}
\int_{p_0}^{p_1} F(p) dp &= \int_{\frac{k}{1+k}p_1}^{p_1} \left(1 - \frac{p_1 - p}{p}k \right) dp \\
&= \int_{\frac{k}{1+k}p_1}^{p_1} \left(1 + k - \frac{p_1}{p}k \right) dp \\
&= \left[(1 + k)p - kp_1 \ln p \right]_{\frac{k}{1+k}p_1}^{p_1} \\
&= p_1 - kp_1 \ln \frac{1 + k}{k}
\end{aligned} \tag{21}$$

Hence

$$p_1 = \frac{c}{1 - k \ln \frac{1+k}{k}} \tag{22}$$

Inserting for $k = \frac{u + \rho I}{(1 - \rho)I}$ gives that

$$p_1 = \frac{c}{1 - \frac{u + \rho I}{(1 - \rho)I} \ln \frac{u + I}{u + \rho I}}$$

No search for $\rho < \rho^*$ (and $\rho_1 = q = 0$) is satisfied if and only if $\kappa = (1 - x^M) (c + (1 - \rho_0)(P^M - p_1)) \leq c$, or

$$\frac{(1-x)\rho}{x+(1-x)\rho} \left(c + (1-\rho) \left(p^M - \frac{c}{1 - \frac{u+\rho I}{(1-\rho)I} \ln \frac{u+I}{u+\rho I}} \right) \right) \leq c \quad (23)$$

Assumption 1 Equation (23) is satisfied for all $\rho < \rho^*$.

A.5 Proof of Proposition 5

Consider first an increase in p^M in the no-search equilibrium. This shifts $\pi_0(\rho_0, 1 - \rho_0, 0)$ upward, while $\pi_2(\rho_0, 1 - \rho_0, q)$ remains unchanged. Furthermore, we know from the proof of Proposition 2 $\pi_0(\rho_0, 1 - \rho_0, q)$ crosses $\pi_0(\rho_0, 1 - \rho_0, 0)$ below. It follows that ρ_0^* increases in p^M . Hence \tilde{u} increases and \tilde{I} decreases, so p^1 increases and F shifts up. It follows that expected transaction prices also increase in p^M .

Consider then an increase in c . This shifts $\pi_2(\rho_0, 1 - \rho_0, 0)$ down, while $\pi_0(\rho_0, 1 - \rho_0, 0)$ remains unchanged. Since $\pi_2(\rho_0, 1 - \rho_0, 0)$ crosses $\pi_0(\rho_0, 1 - \rho_0, 0)$ from below it follows that ρ_0^* decreases. Therefore, π_0 decreases. It follows that π_2 also decreases. Since there is no search, the joint income for sellers and buyers is constant. Hence, expected transaction prices must decrease.

A.6 Proof of Proposition 6

a) Suppose not. Then one can construct a subsequence $\rho(x)$ such that $\lim_{x \rightarrow 0} \rho^*(x) = \hat{\rho} > 0$. It follows that x^M converges to zero. Since a buyer is indifferent between searching and not searching at p_1 , it is sufficient to show that p_1 does not converge to p^M as $x \rightarrow 0$. But that cannot be the case, as it follows from (13) and (14) that the profit at p_1 evaluated at $p_1 = p^M$ is strictly greater than at p^M for strictly positive values of ρ , a contradiction.

To prove the last part, note that at p^{M-} the profit goes to zero as ρ goes to zero, while the profit at p_1 is bounded below by $c(u + I)$. Hence, for sufficiently low values of x and hence ρ , it is not profitable to set a price equal to p^{M-} .

b) Suppose not. Consider a sequence of costs c_n converging to zero, and suppose (a subsequence of) $\rho_0(c_n)$ and $\rho_1(c_n)$ converges to ρ_0^* and ρ_1^* , respectively. If $\rho_0^* + \rho_1^* = 0$, the result follows immediately. Suppose therefore that $\rho_0^* + \rho_1^* > 0$.

Suppose first that $\rho_1^* > 0$. Then q converges to 1, and it is strictly better to set p^{M-} than p^M , hence $\rho_0^* = 0$. It follows that $\pi_0 = 0$, and F_b collapses to 0.

Suppose then that $\rho_1^* = 0$. Suppose first that $\rho_2^* > 0$. Then $p_1^* = 0$, and buyers in a limit equilibrium search with probability 1 at p^M ($q^* = 1$). However, this is not consistent with $\rho_1^* = 0$, see (5).

Suppose therefore instead that ρ_0 goes to 1 and ρ_2 goes to 0. However, this is not consistent with (5) either. This completes the proof.

B Model extensions

B.1 Stochastic collusion price

We still assume that firms 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 $[p^M, 1]$. We assume that $p^M(u + I) \geq u$. Let \mathcal{F} denote the distribution of p .

Proposition 7. *The equilibrium distribution \mathcal{F} has the following properties:*

1. \mathcal{F} has no mass points.
2. The minimum of the support is below p^M .
3. The support of \mathcal{F} consists of at most two distinct intervals; $[p_0, p_1]$ and $[p_2, 1]$, $p^M \geq p_2 \geq p_1$.

The proof is given below.

B.1.1 Proof of proposition 7

\mathcal{F} has no mass points: Suppose it has a mass point at p' . Clearly, $p' \in [p^M, 1]$, otherwise the standard under-cutting argument applies. Suppose therefore that $p' \in [p^M, 1]$. It follows that the posterior probability that there is collusion given that a buyer observes p' is zero. Therefore, the standard under-cutting argument applies also here; if a seller deviates and sets $p' - \varepsilon$, the seller attracts the informed buyers with a strictly higher probability than at

p' , and the uninformed buyers do not search with a higher probability. Hence undercutting pays off, and we cannot be nonequilibrium. It follows that \mathcal{F} does not have a mass point.

\mathcal{F} has support below p^M : Suppose not. The pay-off to a seller at the top of the support is at most u . The pay-off at the infimum of the support is then at least $p^M(I + u)$ (no buyer searches at the infimum of the support). By assumption $p^M(I + u) > u$, therefore we cannot be in equilibrium.

The support of \mathcal{F} consists of at most two distinct sets: Suppose the support of \mathcal{F} consists of more than two distinct sets. Suppose $p_1 < p^M$. Then the buyers are indifferent between buying and not buying at p_1 , and search with probability 1 for any $p \in (p_1, p^M)$. Hence, by the standard argument, \mathcal{F} cannot have a "hole" (p', p'') , p', p'' both in (p_1, p^M) , as it would then be strictly better to set p'' than p' .

Note further that \mathcal{F} cannot have a hole in the support at (p', p'') above p^M either. A seller advertising a price in the hole will then obtain at least the same sales as at p' (since the uninformed buyers will buy) and earn a strictly higher profit, which is inconsistent with equilibrium. \square

B.1.2 A special case

A very intuitive and natural candidate, parallel to the equilibrium in the main model, is one in which the support of \mathcal{F} consists of two sets $[p_0, p_1]$ and $[p^M, 1]$, $p_1 < p^M$, with associated mass $1 - \rho$ and ρ , and contingent distribution functions $F_1(p)$ and $F_2(p)$ on $[p_0, p_1]$ and $[p^M, 1]$, respectively. At p_1 , the buyers are indifferent between searching and not. At p^M , the buyers search with a strictly positive probability (otherwise, sellers would prefer p^M to p_1). At any $p \in [p^M, 1]$, $f_2(p)$ and $q(p)$ adjust so that the sellers obtain the utility $\pi(1)$ (obtained at $p = 1$), with the restriction that

$$(1 - \tilde{x}(p))(c + (1 - \rho)(p - p_1)) + \rho \int_{p^M}^p F_2(p') dp' \leq c \quad (24)$$

where $\tilde{x}(p) = \frac{xg(p)}{xg(p) + (1-x)\rho f(p)}$ is the posterior probability that there is collusion given p , analogous to x^M given by (7) in the main text. Equation (24) is analogous to equation (8) in the main text. The left-hand side gives the gain from search at p . As in the main model,

a complementary slackness condition holds: If the inequality is slack, $q(p) = 0$, if it is strict, $q(p) \geq 0$. In order to equalise profits (for given ρ), f_2 adjusts up to the point at which (24) binds, at which points $q(p)$ starts to adjust.

B.2 Many sellers

Suppose that there are $n \geq 2$ sellers in the market. The structure of the equilibrium is unaltered. We focus on equilibria with $\rho_1 = 0$.

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

Profits when setting $p \in [p_0, p_1]$ can be written as

$$\pi(p) = p \{u + [\rho + (1 - \rho)(1 - F(p))]^{n-1} I\} \quad (25)$$

At the interval $[p_0, p_1]$, profit must be equal, which implies that

$$p \{u + [\rho + (1 - \rho)(1 - F(p))]^{n-1} I\} = p_1(u + \rho^{n-1} I)$$

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

$$1 - F(p) = \frac{\left[\frac{(p_1 - p)u + p_1 \rho^{n-1} I}{pI} \right]^{\frac{1}{n-1}} - \rho}{1 - \rho} \quad (26)$$

The equilibrium candidate without search can be written as

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

$$p^M \left(u + \rho^{n-1} \frac{I}{n} \right) = p_1(u + \rho^{n-1} I) \quad (27)$$

2. Equal profits for all $p \in [p_0, p_1]$, $F(p)$ given by (26). As above p_0 is defined by $F(p_0) = 0$.

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

$$(1 - \rho) \int_{p_0}^{p_1} F(p) dp = c \quad (28)$$

If the solution to (28) is greater than 1, then $p_1 = 1$.

Note that the equation for p_1 , (28), 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 $x^M = \frac{x}{x+(1-x)\rho}$ (by Bayes law), as before. And as before, the gain from search is $(1 - \rho)((1 - \rho)(p^M - p_1))$ higher than the gain from search at p_1 . Hence, the condition for no search is still given by (8).

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 still given by (25), but with u replaced by $\tilde{u} = u(1 + (1 - n)\rho q)$. Hence the equilibrium candidate with search can be written as

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

$$p^M(u(1 - q) + I\rho^{n-1}/n) = p_1(u(1 + (1 - n)q\rho) + \rho^{n-1}I) \quad (29)$$

2. Equal profits for all $p \in [p_0, p_1]$, implying that $F(p)$ is given by (26) with u replaced by $u(1 + (n - 1)\rho q)$. p_0 is defined by $F(p_0) = 0$.

3. Consumers at p_1 are indifferent between searching and not searching, satisfying (28).

If the solution to (28) is greater than 1, then $p_1 = 1$

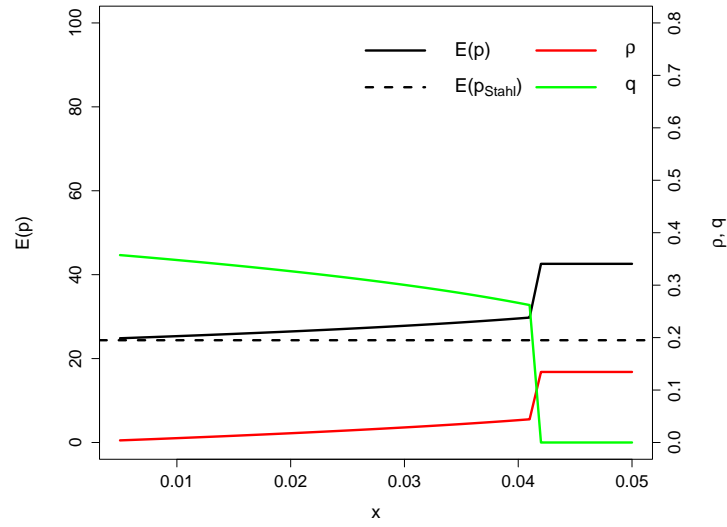
4. Consumers at p^M are indifferent between searching and not searching, satisfying (9) with equality.

C Simulations

In the following we present results from four numerical simulations. One in which we vary the probability of collusion (x), one in which we vary the search cost (c), one in which we vary the collusion price (p^M), and one in which we vary the number of informed buyers (I). For each simulation, we keep the other parameter values at the same levels as in the experiment. We report the expected posted price, both in the Stahl model ($E(p_{Stahl})$) and in the model with possible collusion ($E(p)$), the probability that the price is set to P^M (ρ), and the probability of search at P^M (q).

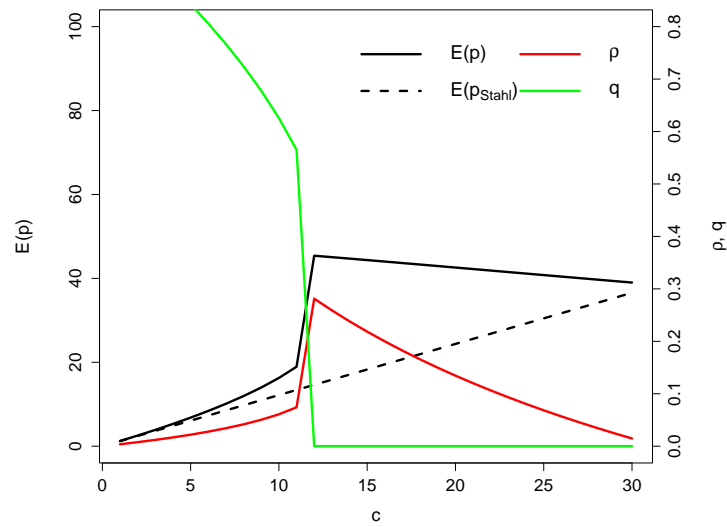
Some features deserve attention. First, the equilibrium without search exists even for low probabilities of collusion, see Figure 8. Given the parameter values in the experiment, the no-search equilibrium exists for $x > 0.041$. For lower priors on the probability of collusion, there is search in equilibrium. Second, the impact of possible collusion (defined as the difference in expected prices between our possible collusion model and the Stahl model) is highest for intermediate search costs; see Figure 9. For low search costs, there is search in the equilibrium with possible collusion, which in turn dampens the impact of possible collusion. For higher search costs, there is no search, and the price is decreasing with search costs in the possible collusion equilibrium while the price increases with search costs in the Stahl model. Third, the impact of possible collusion is increasing in the collusive price level, see Figure 10. Finally, the impact of possible collusion is high for $\frac{I}{2} > u$, while it is low for $\frac{I}{2} < u$ as both the Stahl price and the price in the possible collusion equilibrium approach the monopoly price when I approaches zero, see Figure 11.

Figure 8: Equilibrium for different probabilities of collusion (x)



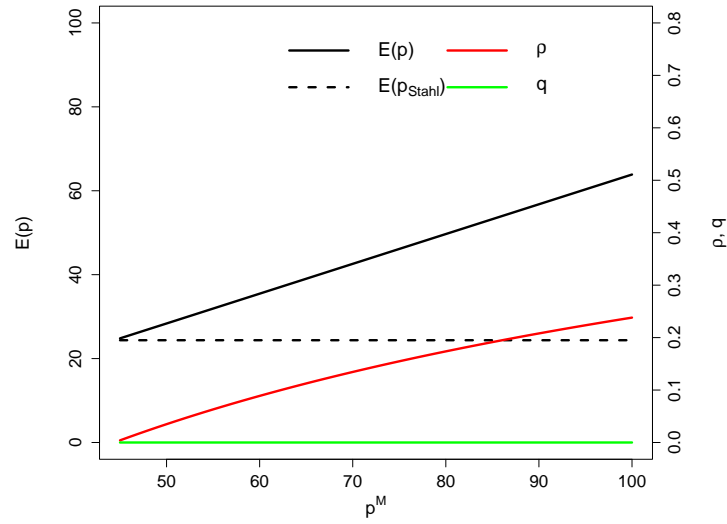
Other parameter values: $u = 1$, $I = 2$, $c = 20$ and $p^M = 70$.

Figure 9: Equilibrium for different search costs (c)



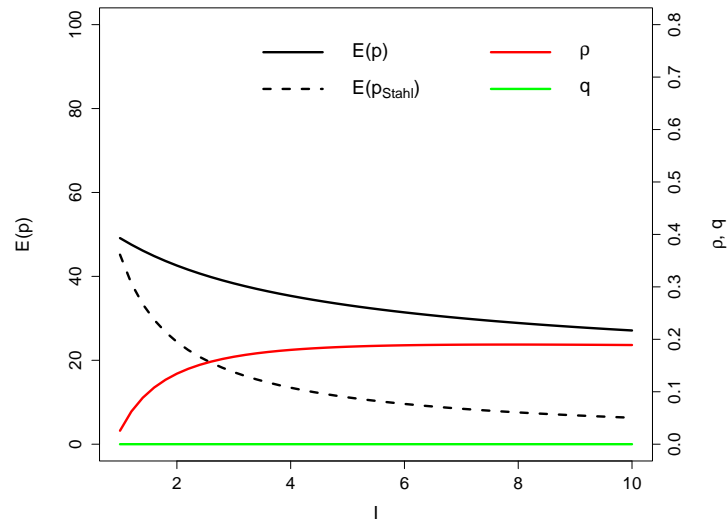
Other parameter values: $u = 1$, $I = 2$, $x = 0.2$ and $p^M = 70$.

Figure 10: Equilibrium for different collusion prices (p^M)



Other parameter values: $u = 1$, $I = 2$, $c = 20$ and $x = 0.2$.

Figure 11: Equilibrium for different numbers of informed buyers (I)



Other parameter values: $u = 1$, $p^M = 70$, $c = 20$ and $x = 0.2$.

D Results

D.1 Inference: Last 20 games

Table 12: 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 where the price was set exogenously are excluded.

Table 13: 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 where the price was set exogenously are excluded.

Table 14: 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 15: 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 where the price was set exogenously are excluded.

Table 16: 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 where the price was set exogenously are excluded.

D.2 Results and inference: All games

Table 17: 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 where the price was set exogenously are excluded from average price and share of posted prices at 70 ECU.

Table 18: 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 where the price was set exogenously are excluded.

Table 19: 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 where the price was set exogenously are excluded.

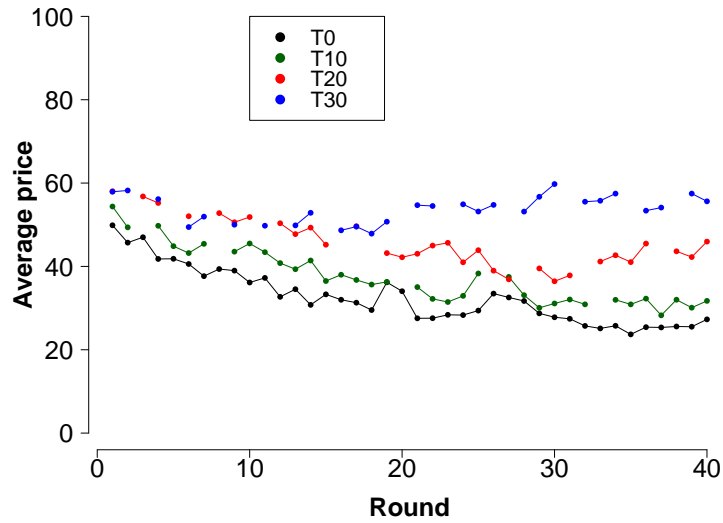
Table 20: Wilcoxon rank-sum test (p -values): Share who search.

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

Note: First 20 games are excluded.

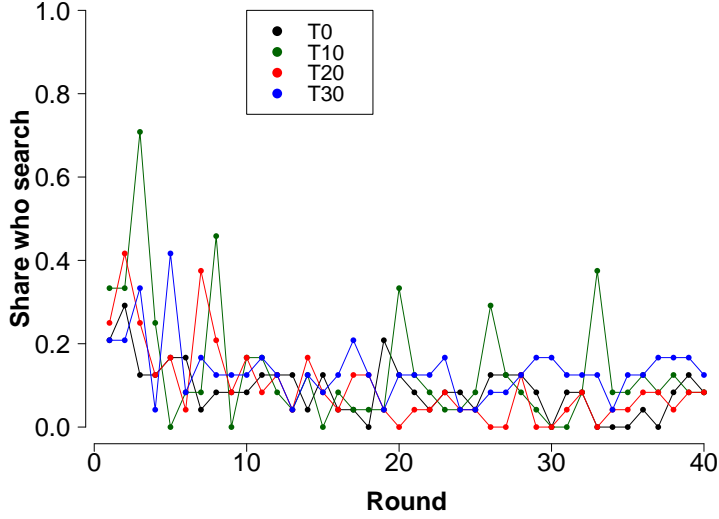
D.3 Results by round

Figure 12: Average price by game and treatment



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

Figure 13: Search behaviour by game and treatment



E 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

$$A_i^{Seller}(t) = \begin{cases} \phi_{Seller} A_i^{Seller}(t-1) + \pi(t) & \text{if } p(t) \in P_i \\ \phi_{Seller} A_i^{Seller}(t-1) & \text{otherwise} \end{cases} \quad (30)$$

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

$$Pr_i(t) = \frac{\exp(\lambda_{Seller} A_j^{Seller}(t-1))}{\sum \exp(\lambda_{Seller} A_i^{Seller}(t-1))} \quad (31)$$

where λ_{Seller} represents sensitivity to attraction.

When fitting the model we consider five different price ranges: $[0, 26.5)$, $[26.5, 62.6)$,

(62.6, 70), 70 and (70, 100].³³ We estimate initial attraction $A_i^{Seller}(0)$, ϕ_{Seller} , and λ_{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 21. The recency parameters indicate that learning is not too persistent and that more recent payoffs carry more weight than more distant ones. Furthermore, λ_{Seller} is statistically above 0 in all treatments, indicating that learning matters.

Table 21: Model estimates

Parameter	T10	T20	T30
ϕ_{Seller}	0.709 (0.022)	0.722 (0.031)	0.689 (0.027)
λ_{Seller}	0.019 (0.002)	0.013 (0.002)	0.012 (0.001)
$A_1^{Seller}(0)$	0 (normalised)	0 (normalised)	0 (normalised)
$A_2^{Seller}(0)$	102.049 (30.427)	947.589 (528.944)	288.938 (86.628)
$A_3^{Seller}(0)$	14.150 (36.015)	826.982 (531.896)	116.283 (93.528)
$A_4^{Seller}(0)$	25.617 (35.015)	865.832 (531.117)	235.910 (86.850)
$A_5^{Seller}(0)$	-34.261 (45.050)	770.625 (535.487)	116.2836 (94.413)

Note: Standard errors in parentheses. Rounds in which the price was set exogenously are not included in the estimation.

F 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 different measures: Average price across games by subject and share of posted prices at 70 ECU across games by subject.

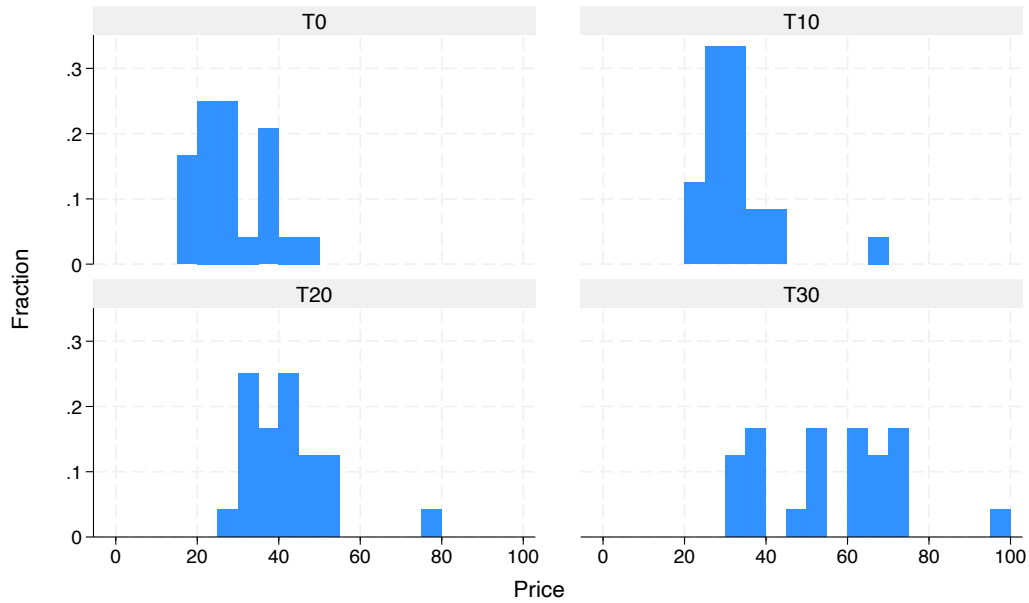
F.1 Average price

Figure 14 presents the distribution of the average price by subject in our four treatments. As the figure shows, there is heterogeneity in the average pricing behaviour of subjects. Average

³³The model becomes difficult to estimate with more granular ranges.

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 14: Distribution of average price by subject.

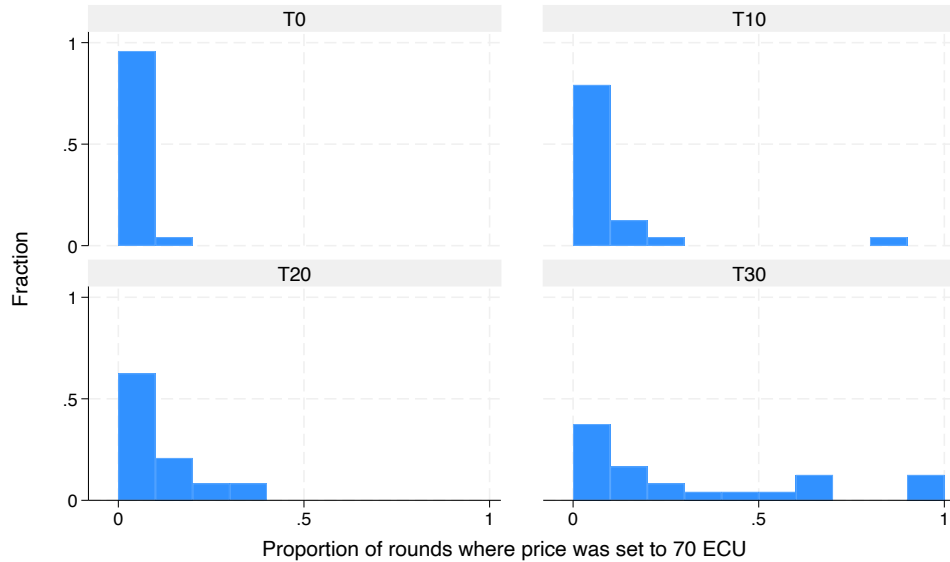


Note: Bin size=5. First 20 games and games where the price was set exogenously are excluded.

F.2 Share of posted prices at 70 ECU

Figure 15 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 of the subjects or more never post a price of 70 ECU. However, in treatment $T30$, more than half of subjects post a price of 70 ECU at least twice.

Figure 15: Distribution of propensity to post a price of 70 ECU by subject.



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

G Sample instructions

G.1 Instructions T0

Welcome! You are participating in an experiment financed by the Department of Economics at BI and the Norwegian Research Council.

You will earn money in the experiment. 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 experiment.

All participants in the experiment are present in this room. 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 not allowed to communicate with participants in the room until the experiment is over. Also we ask that you do not use your cellphones during the experiment.

In the experiment your payoffs are denominated in ECU. At the end of the experiment, you will be paid in Norwegian Kroner (NOK) based on your earnings in ECU. The exchange rate from ECU to NOK is:

$$1 \text{ ECU} = 2 \text{ NOK}$$

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

At the end of the experiment you will fill in your full name and your phone number in a screen on your computer. This is for payment purposes only. After payments have been made your full name and your phone number are permanently deleted from our records, so complete anonymity is guaranteed in all subsequent analysis of the data collected in this experiment.

The experiment

In this experiment each of you will be assigned a role as either a *seller* or a *buyer*. These roles remain fixed throughout the experiment.

The game

The experiment consists of 40 identical and independent games. In each game, two sellers and two buyers are randomly matched to form a *market*.

Each game progresses as follows:

- **The sellers' decision:** Each seller simultaneously sets a price between 0 ECU and 100 ECU.
- **The buyers' decision:**
 - A buyer observes the price of *one* of the sellers in his/her market, while the other buyer observes the price of the *other* seller.
 - Buyers can choose to purchase at the observed price *or* to pay a cost of 20 ECU to also observe the price of the other seller in the market.

– If a buyer pays to observe the price of the other seller, the buyer purchases from the other seller only if that seller has a lower price.

- **Additional sales:** The seller with the lowest price in a market will make two additional sales. These additional sales do not depend on the decisions of buyers nor do they affect buyers' payoffs.

If both sellers have the same price, each seller sells to one buyer and make one additional sale.

After each game, sellers and buyers receive feedback on prices set and ECUs earned.

After a game is completed, buyers and sellers are randomly re-matched into a new market and a new game begins.

Payoffs

Seller payoffs:

The seller with the highest price in the market: The payoff of this seller is $1 \cdot Price$ if the buyer who initially observes this seller's price does not pay to observe the other seller's price, and zero otherwise.

The seller with the lowest price in the market: The payoff of this seller is $3 \cdot Price$ if only one buyer observes his/her price, and the payoff is $4 \cdot Price$ if both buyers observe his/her price.

Both sellers have the same price: In this case, the payoff to each seller is $2 \cdot Price$.

Buyer payoffs:

If the buyer chooses not to observe the price of the other seller, the payoff is $100 - Price$.

If the buyer chooses to pay to observe the price of the other seller, the payoff is $100 - 20 - Lowest\ price$.

Earnings from the experiment

At the end of the experiment, two games will be picked at random to determine your earnings from this experiment. Your total earnings from the experiment will be the sum of ECUs earned in these two games plus 40 ECU. Your earnings will be converted to NOK and transferred to your Vipps account.

Are there any questions?

G.2 Instructions T20

Welcome! You are participating in an experiment financed by the Department of Economics at BI and the Norwegian Research Council.

You will earn money in the experiment. 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 experiment.

All participants in the experiment are present in this room. 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 not allowed to communicate with participants in the room until the experiment is over. Also we ask that you do not use your cellphones during the experiment.

In the experiment your payoffs are denominated in ECU. At the end of the experiment, you will be paid in Norwegian Kroner (NOK) based on your earnings in ECU. The exchange rate from ECU to NOK is:

$$1 \text{ ECU} = 2 \text{ NOK}$$

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

At the end of the experiment you will fill in your full name and your phone number in a screen on your computer. This is for payment purposes only. After payments have been

made your full name and your phone number are permanently deleted from our records, so complete anonymity is guaranteed in all subsequent analysis of the data collected in this experiment.

The experiment

In this experiment each of you will be assigned a role as either a *seller* or a *buyer*. These roles remain fixed throughout the experiment.

The game

The experiment consists of 40 identical and independent games. In each game, two sellers and two buyers are randomly matched to form a *market*.

Each game progresses as follows:

- **The sellers' decision:** Sellers either decide on a price themselves, or it is set for them by the computer.
 - When sellers decide on a price themselves, each seller simultaneously sets a price between 0 ECU and 100 ECU.
 - When the price is set by the computer, the price is set to **70 ECU** for *both* sellers in the market.
 - The probability that the price is set by the computer is 20 percent in each game.
 - Buyers do not know whether the price is set by the computer or by the sellers.

- **The buyers' decision:**
 - A buyer observes the price of *one* of the sellers in his/her market, while the other buyer observes the price of the *other* seller.
 - Buyers can choose to purchase at the observed price *or* to pay a cost of 20 ECU to also observe the price of the other seller in the market.

– If a buyer pays to observe the price of the other seller, the buyer purchases from the other seller only if that seller has a lower price.

- **Additional sales:** The seller with the lowest price in a market will make two additional sales. These additional sales do not depend on the decisions of buyers nor do they affect buyers' payoffs.

If both sellers have the same price, each seller sells to one buyer and make one additional sale.

After each game, sellers and buyers receive feedback on prices set and ECUs earned. Buyers are not informed about whether the price is set by the computer or by the sellers.

After a game is completed, buyers and sellers are randomly re-matched into a new market and a new game begins.

Payoffs

Seller payoffs:

The seller with the highest price in the market: The payoff of this seller is $1 \cdot Price$ if the buyer who initially observes this seller's price does not pay to observe the other seller's price, and zero otherwise.

The seller with the lowest price in the market: The payoff of this seller is $3 \cdot Price$ if only one buyer observes his/her price, and the payoff is $4 \cdot Price$ if both buyers observe his/her price.

Both sellers have the same price: In this case, the payoff to each seller is $2 \cdot Price$.

Buyer payoffs:

If the buyer chooses not to observe the price of the other seller, the payoff is $100 - Price$.

If the buyer chooses to pay to observe the price of the other seller, the payoff is $100 - 20 - Lowest\ price$.

Earnings from the experiment

At the end of the experiment, two games will be picked at random to determine your earnings from this experiment. Your total earnings from the experiment will be the sum of ECUs earned in these two games plus 40 ECU. Your earnings will be converted to NOK and transferred to your Vipps account.

Are there any questions?