Online Appendix

for the paper: *Algorithmic Price Recommendations and Collusion: Experimental Evidence*

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Appendix A Theoretical framework

In this section, we provide further details on the theoretical background of the market environment that we consider. We show the Nash equilibrium of the stage game. Furthermore, we prove that following the recommendation by RecTheory constitutes a subgame perfect Nash equilibrium while it does not for RecSoft.

A.1 Setting and Nash equilibria

We consider an infinitely repeated Bertrand game with $n \geq 2$ symmetric sellers denoted by A, B, and so on. Each seller aims at maximizing its profit and discounts future profit flows with a discount factor of δ.

In each period, each seller chooses its price from the integers in the set $P = \{p^N, p^N + 1, ..., p^M\} \subset \mathbb{Z}^+$. There are k consumers who are willing to buy one unit of the good each and are willing to pay p^M per unit. The seller with the lowest price in a given period supplies the entire market. If multiple sellers have the lowest price, they share the market equally.

The sellers have no costs and no capacity constraints. Note that abstracting from costs does not change the insights from this analysis. We would get qualitatively the same results if we explicitly modeled costs which, in reality, may include commission payments.

What matters for the analysis is that there is a range of prices between the relatively low competitive price level and a collusive price at which all firms make strictly higher profits.

Nash equilibrium of the stage game. Suppose that, except for seller A, all sellers set prices larger than p^N and at least at a level of p. Notice that seller A makes zero profits for any price higher than p, whereas setting a price of p yields a profit of $p \cdot k/n$. On the other hand, a deviation to $p-1$ yields a profit of $(p-1) \cdot k$. Undercutting the lowest price of a competitor, p, by one unit is the best response if

$$
\begin{aligned}
& (p-1) \cdot k > p \cdot k/n \\
\implies & (p-1) > p \cdot 1/n \\
\implies & p \cdot (1 - 1/n) > 1 \\
\implies & p > n/(n-1).
\end{aligned}
$$

We define p^N as the integer weakly below $n/(n-1)$. At this price, no firm has an incentive to undercut, such that each firm setting a price of p^N and making a profit of $p^N \cdot k/n$ is a Nash equilibrium. For $n = 3$, there is a strict incentive to undercut any price larger than 1.5, such that $p^N = 1$. As $n/(n-1)$ is decreasing in n, it follows that $p^N = 1$ for any market with $n > 3$. For $n = 2$, both a symmetric price of 1 and a symmetric price of 2 constitute a Nash equilibrium.[32]

Collusive equilibrium of the repeated game. We now construct a collusive subgame perfect Nash equilibrium of the infinitely repeated game with trigger strategies. In line with the Folk Theorem, multiple collusive equilibria potentially exist. Variations are possible in the collusive price level and the punishment scheme. For instance, any price above the competitive price can potentially be supported as a collusive outcome. We focus on the highest and most profitable collusive price of p^M. Among the equilibria with Nash-

[32] For $n = 2$, there is a strict incentive to undercut any (integer) price larger than 2, such that $p^N = 2$. A symmetric price of 1 is also a Nash equilibrium, but there is no strict incentive to undercut a symmetric price of 2 either as $1 \cdot k = 2 \cdot k/2$.

reversion, we focus on the equilibrium with the shortest possible punishment length. As we explain in Section 2, behavioral evidence indicates that punishments are often relatively soft.

Suppose the collusive strategy is as described by the RecTheory algorithm in Section 2. In other words, firms collude at the monopoly price and punish deviations by choosing the stage game Nash equilibrium for T periods. In period $T+1$ the firms revert back to the monopoly price.

The strategy yields the stability condition

$$\pi^M \cdot (1+\delta+\delta^2+...) \geq \pi^D + \sum_{t=1}^{T} \delta^t \pi^N + \pi^M \cdot (\delta^{T+1}+\delta^{T+2}...),$$

where π^M is the collusive period profit, π^D the deviation profit and π^N the static Nash profit as the punishment profit.

Rearranging yields

$$\pi^M \cdot (1+\delta+\delta^2+...+\delta^T) \geq \pi^D + \pi^N \cdot \sum_{t=1}^{T} \delta^t$$
$$\Leftrightarrow \sum_{t=1}^{T} \delta^t \geq \frac{\pi^D - \pi^M}{\pi^M - \pi^N}.$$

Suppose the latter condition holds with equality. A lower discount factor requires more punishment periods T for collusion to be stable. Similarly, a higher gain from deviating requires more punishment periods as well.

Parameter values in the experiment. In the experiment, we have $p^M = 10$, k=30, n=3, and consequently $p^N = 1$. We use a value of 0.95 for the discount factor δ as this equals the continuation probability in our experiment, which we introduce in Section 2. To determine the shortest punishment length T that makes collusion stable for these parameters, we plug in the values for the profits:

$$\pi^M = 10 \cdot 30/3 = 100;$$
$$\pi^D = 9 \cdot 30 = 270;$$
$$\pi^N = 1 \cdot 30/3 = 10.$$

This yields

$$\sum_{t=1}^{T} \delta^t \geq \frac{270 - 100}{100 - 10} \approx 1.89.$$

The left-hand side is equal to $\delta = 0.95$ for a one-period punishment, $\delta + \delta^2 = 1.85$ for a two-period punishment, and $\delta + \delta^2 + \delta^3 = 2.59$ for a three-period punishment, respectively. Hence, three punishment periods, T, are necessary and sufficient for the stability condition to hold and for the trigger strategy to constitute a subgame perfect Nash equilibrium of the infinitely repeated stage game. As the trigger strategy mimics the recommendations by RecTheory, it is also a subgame perfect Nash equilibrium to follow the recommendations of the algorithms, conditional on the belief that other participants will also follow the recommendation.

A.2 Behaviourally motivated soft punishment algorithms

We show that following the recommendations of the algorithm RecSoft does not constitute a subgame perfect Nash equilibrium. To see this, suppose that all sellers follow the recommendations throughout the game. If seller A follows the recommendations, the per-period profit is $p^M \cdot k/n$ in each period, yielding a profit stream of

$$p^M \cdot k/n \cdot (1 + \delta + \delta^2 + \delta^3 + ...).$$

Consider a one-shot deviation of setting a price of $p_A < p^M$ while the algorithm recommends a price of p^M. The profit in the deviation period equals $p_A \cdot k$. The algorithm recommends a price of p_A in the next period. All sellers that follow the recommendation receive a profit of $p_A \cdot k/n$. Afterward, the algorithm reverts to the monopoly price of p^M. Thus, the deviating seller obtains a deviation profit of $p_A \cdot k$ for one period and a punishment profit of $p_A \cdot k/n$ for another period. Hence, the profit stream is

$$p_A \cdot k + p_A \cdot k/n \cdot \delta + p^M \cdot k/n \cdot (\delta^2 + \delta^3 + ...),$$

which is highest for the highest feasible deviation price of $p_A = p^M - 1$. The difference between the deviation profit stream and the collusion profit stream is

$$k \cdot (p_M \cdot (1 - 1/n) - 1 - 1/n \cdot \delta).$$

Thus, deviating from the recommendation is profitable if

$$p^M > \frac{n + \delta}{n - 1}.$$

For $n \geq 2$ and $\delta < 1$ the condition holds for any $p^M > 2$. Thus, following the recommendation does not constitute a subgame perfect Nash equilibrium for the parameters used in the experiment as $p^M = 10$.

Appendix B Instructions and post-experimental questionnaire

The experiment was conducted in German. Below, we provide the original version of the instructions as well as a translation. Furthermore, we provide the post-experimental questionnaire.

B.1 Instructions (Original)

Hallo und herzlich willkommen zu unserem Experiment. In der nächsten Stunde werden Sie an einem Computer Entscheidungen treffen. Bitte lesen Sie die Instruktionen aufmerksam durch. Alle Teilnehmer erhalten die gleichen Instruktionen. Eine Kopie dieser Instruktionen finden Sie auch ausgedruckt an Ihrem Platz. Sie bleiben für uns und für die anderen Experimentteilnehmer völlig anonym. Wir speichern keine Daten, die mit Ihrem Namen in Verbindung stehen.

Besonders wichtig: Sprechen Sie nicht mit Ihren Nachbarn, benutzen Sie nicht Ihr Mobiltelefon und verhalten Sie sich während des gesamten Experiments leise. Sollten Sie irgendwelche Fragen haben, melden Sie sich. Wir kommen dann zu Ihrem Platz und helfen.

In diesem Experiment treffen Sie wiederholt Preisentscheidungen. Diese ermöglichen es Ihnen echtes Geld zu verdienen. Wie viel Sie verdienen ist abhängig von Ihren Entscheidungen und denen Ihrer Mitspieler. **Unabhängig davon erhalten Sie 4,00 Euro für die Teilnahme.**

Im Experiment verwenden wir eine fiktive Geldeinheit namens Taler. Im Anschluss an das Experiment werden die Taler in Euro umgerechnet und Ihnen ausgezahlt. **Dabei entsprechen 100 Taler einem Euro.** Die Euro-Beträge werden auf die erste Nachkommastelle gerundet.

Beispiel:
Teilnehmer A hat im Experiment 465 Taler verdient. Umgerechnet entspricht das 4,65 Euro. Auf die erste Nachkommastelle gerundet werden Teilnehmer A 4,70 Euro ausgezahlt.

Erläuterungen

In diesem Spiel repräsentieren Sie eine Firma in einem virtuellen Produktmarkt. In dem Markt verkaufen zwei weitere Firmen das gleiche Produkt wie Sie. Diese Firmen werden von zwei anderen Experiment-Teilnehmern repräsentiert. Das Spiel hat mehrere Runden. Sie treffen in jeder Runde des Spiels auf dieselben Firmen (also Experiment-Teilnehmer).

Alle Firmen entscheiden in jeder Runde erneut **eigenständig und gleichzeitig,** für wie viele Taler Sie Ihr Produkt verkaufen möchten. Sie können Ihr Produkt für einen Peis von 1, 2, ... oder 10 Taler verkaufen (nur ganze Taler). **Es gibt keine Produktionskosten.** Ihr Gewinn ist das Produkt aus Preis und der Anzahl verkaufter Einheiten. Formal ausgedrückt:

Gewinn = Preis x verkaufte Einheiten.

Der Markt hat 30 identische Kunden. Jeder Kunde möchte in jeder Runde eines Spiels **eine Einheit** des Produkts möglichst günstig kaufen. Jeder Kunde ist bereit bis zu 10 Taler für diese Einheit des Produkts auszugeben.

Die Firma mit dem **niedrigsten Preis in der jeweiligen Runde** verkauft Ihre Produkte. **Der niedrigste Preis ist also der Marktpreis in der jeweiligen Runde**. Firmen mit einem **Preis, der größer als der Marktpreis ist, verkaufen Ihre Produkte in der jeweiligen Runde nicht und erhalten daher einen Gewinn von Null.** Sollten zwei oder alle drei Firmen Ihr Produkt für den gleichen Marktpreis verkaufen wollen, teilt sich die Nachfrage gleichmäßig auf die zwei bzw. drei Firmen auf.

Beispiele Beispiel 1 Firma A setzt einen Preis von 4, Firma B setzt einen Preis von 4, Firma C setzt einen Preis von 6. Somit haben Firma A und B gemeinsam den niedrigsten Preis gesetzt. Firma A und B verkaufen beide die gleiche Anzahl an Produkten, beide Firmen haben jeweils 15 Kunden und bekommen damit den gleichen Gewinn von 60 Talern. Firma C verkauft nichts und hat einen Gewinn von 0.

	Firma A	Firma B	Firma C
Preise	4	4	6
Gewinne	60	60	0

Beispiel 2: Firma A setzt einen Preis von 7, Firma B setzt einen Preis von 7, Firma C setzt einen Preis von 7. Somit haben Firma A, B und C gemeinsam den niedrigsten Preis gesetzt. Sie verkaufen alle die gleiche Anzahl an Produkten (jeweils 10) und bekommen damit den gleichen Gewinn von 70 Talern.

	Firma A	Firma B	Firma C
Preise	7	7	7
Gewinne	70	70	70

Beispiel 3: Firma A setzt einen Preis von 1, Firma B setzt einen Preis von 4, Firma C setzt einen Preis von 10. Somit hat Firma A den niedrigsten Preis gesetzt. Firma A verkauft als einzige das Produkt zu einem Preis von 1 an alle 30 Kunden und bekommt damit einen Gewinn von 30 Talern. Firma B und C verkaufen beide nichts und haben einen Gewinn von 0.

	Firma A	Firma B	Firma C
Preise	1	4	10
Gewinne	30	0	0

Preisempfehlungen

Bevor Sie in jeder Runde Ihren Preis wählen, erhalten Sie von einem Computeralgorithmus eine konkrete **Preisempfehlung**. **. Alle drei Firmen im Markt erhalten dieselbe Preisempfehlung.**

Der Algorithmus zielt darauf ab, die **Gesamtgewinne aller Firmen über alle Runden hinweg zu maximieren.** Es wird Ihnen also eine Empfehlung ausgesprochen, die allen Firmen langfristig den größtmöglichen Gewinn ermöglicht. Der Algorithmus empfiehlt somit **nicht** zwangsläufig einen Preis, der den höchstmöglichen Gewinn in einer einzelnen Runde erzielt. **Es werden Preise empfohlen, die insgesamt über das gesamte Spiel einen hohen Gesamtgewinn erzielen.**

Der Algorithmus selbst ist kein Marktteilnehmer und kann auch keinen Gewinn generieren,

er dient nur als Information für alle Teilnehmer.

Wichtig: Bei der Preisempfehlung handelt es sich lediglich um einen **Vorschlag**. Es steht Ihnen frei, einen anderen Preis als den empfohlenen zu setzen.

Dauer des Experiments

Nach jeder Runde werden alle Firmen über die gewählten Preise aller drei Firmen und ihren eigenen Gewinn informiert. In der nächsten Runde hat jede Firma wieder die Möglichkeit ihren Preis neu zu wählen. Sie interagieren in jeder Runde innerhalb eines Spiels mit denselben Teilnehmern.

Nach jeder Runde entscheidet ein Zufallsmechanismus, ob eine weitere Runde gespielt wird oder das Spiel endet. Die Wahrscheinlichkeit, dass eine weitere Runde gespielt wird, liegt bei 95 %. Das Spiel endet also nach jeder Runde mit einer Wahrscheinlichkeit von 5 %.

Bildlich gesprochen wirft der Computer vor jeder möglichen weiteren Runde einen virtuellen Würfel mit 20 Seiten. Das Ergebnis entscheidet, ob eine weitere Runde gespielt wird oder nicht. Bei einer Zahl von 20 ist das Spiel vorbei, bei allen anderen Zahlen wird eine weitere Runde gespielt.

Beachten Sie:

Sie spielen das beschriebene Spiel insgesamt drei mal. Nach jedem Spiel werden sie mit neuen Teilnehmern zu einem neuen Markt zusammengesetzt. Das bedeutet, dass Sie in jedem der drei Spiele mit anderen Teilnehmern interagieren.

Nachdem alle Spiele beendet sind, wird zufällig entschieden, welches der drei Spiele ausgezahlt wird. Diesen Gewinn erhalten Sie im Anschluss an das Experiment. Außerdem erhalten Sie zusätzlich 4,00 Euro für die Teilnahme an diesem Experiment.

Als Hilfsmittel blenden wir Ihnen einen virtuellen Taschenrechner ein, mit dem Sie Ihren Gewinn pro Runde berechnen können.

Kontrollfragen

Frage 1: Wie viele Kunden gibt es im Markt, die das Produkt kaufen wollen?

- 25
- 35
- 30
- 40

Frage 2: Was ist die Wahrscheinlichkeit, dass nach Abschluss einer Runde eine weitere Runde gespielt wird?

- 95%
- 5%
- 50%

Frage 3: Sie sind Firma A und wählen einen Preis von 2, Firma B wählt einen Preis von 10, Firma C wählt einen Preis von 9. Was ist Ihr Gewinn in Talern in dieser Runde?

Frage 4: Sie sind Firma A und wählen einen Preis von 8, Firma B wählt einen Preis von 8, Firma C wählt einen Preis von 8. Was ist Ihr Gewinn in Talern in dieser Runde?

Frage 5: Sie haben einen Gewinn von 650 Talern, was ist Ihr Gewinn in Euro?

Frage 6: Welches Ziel verfolgt der Algorithmus?

- Gewinne für alle Firmen in einer einzelnen Runde zu maximieren

- Gesamtgewinne über alle Runden hinweg für alle Firmen zu maximieren
- Gesamtgewinne über alle Runden hinweg für einzelne Firmen zu maximieren
- Gewinne für einzelne Firmen in einer einzelnen Runde zu maximieren

B.2 Instructions (English)

Hello and welcome to our experiment. In the next hour, you will make decisions on a computer. Please read the instructions carefully. All participants will receive the same instructions. You will also find a printed copy of these instructions at your seat. You will remain completely anonymous to us and to the other experiment participants. We will not save any data associated with your name.

Particularly important: Do not talk to your neighbors, do not use your cell phone, and keep quiet throughout the experiment. If you have any questions, please let us know. We will then come to your site and help.

In this experiment, you will repeatedly make pricing decisions. These allow you to earn real money. How much you earn depends on your decisions and on those of your fellow players. **Regardless, you will receive 4.00 euros for participating.**

In the experiment, we use a fictional monetary unit called ECU. After the experiment, the ECU will be converted to euros and paid to you. **Here, 100 ECU equal one euro.** The euro amounts are rounded to the first decimal place.

Example:
Participant A earned 465 ECU in the experiment. Converted, this is equal to 4.65 euros. Rounded to the first decimal place, Participant A is paid 4.70 euros. **Explanations**

In this game you represent a company in a virtual product market. In the market, two other companies sell the same product as you do. These companies are represented by two other experiment participants. The game has several rounds. You will meet the same companies (i.e. experiment participants) in each round of the game.

All companies decide again **independently and simultaneously** in each round,for how many ECU you want to sell your product. You can sell your product for a price of 1, 2, ... or 10 ECU to sell(whole units only). **There are no costs of production.** Your profit is the product of price and the number of units sold. In formal terms:

Profit = price x units sold.

The market has 30 identical customers. Each customer wants to buy **one unit** of the product as cheaply as possible in each round of a game. Each customer is willing to spend up to 10 ECU for that unit of the product.

The company with the **lowest price in the respective round** sells its products. **So the lowest price is the market price in that round**. Firms with a **price greater than the market price do not sell any products in that round and therefore receive a profit of zero.** If two or all three firms want to sell their product for the same market price, the demand is split evenly between the two or three firms.

Examples Exampe 1 Firm A sets a price of 4, Firm B sets a price of 4, Firm C sets a price of 6. Thus, Firms A and B together have set the lowest price. Firms A and B both sell the same amount of products, both firms have 15 customers each and thus get the same profit of 60 ECU. Firm C sells nothing and has a profit of 0.

	Firm A	Firm B	Firm C
Prices	4	4	6
Profits	60	60	0

Example 2: Firm A sets a price of 7, Firm B sets a price of 7, Firm C sets a price of 7. Thus, Firms A, B and C together have set the lowest price. They all sell the same amount of products (10 each) and thus get the same profit of 70 ECU.

	Firm A	Firm B	Firm C
Prices	7	7	7
Profits	70	70	70

Example 3: Firm A sets a price of 1, firm B sets a price of 4, firm C sets a price of 10. Thus, firm A has set the lowest price. Firm A is the only one that sells the product at a price of 1 to all 30 customers and thus gets a profit of 30 ECU. Firms B and C both sell nothing and have a profit of 0.

	Firm A	Firm B	Firm C
Prices	1	4	10
Profits	30	0	0

Price recommendations

Before you choose your price in each round, you receive a specific **price recommendation** from a computer algorithm. **All three firms in the market receive the same price recommendation.**

The algorithm aims to **maximize the total profits of all firms across all rounds**. Therefore, you will be given a recommendation that will allow all firms to make the highest possible profit in the long run. This means that the algorithm does **not** necessarily recommend a price that achieves the highest possible profit in a single round. **It recommends prices that achieve a high total profit over the entire game.**
The algorithm itself is not a market participant and cannot generate profits, **it only serves as information for all participants**.

Note: The recommended price is only a **proposal**. You are free to set any other price than the recommended one.

Duration of the experiment

After each round, all firms are informed about the chosen prices of all three firms and their own profits. In the next round, each firm has again the opportunity to choose their price. You interact with the same participants in each round within a game.

After each round, a random mechanism decides whether another round is played or the game ends. The probability that another round will be played is 95%. The game therefore ends after each round with a probability of 5%.
In other words, the computer throws a virtual dice with 20 sides before each possible further round. The result decides whether another round is played or not. With the number 20, the game is over, with all other numbers, another round is played.

Note:
You play the described game a total of three times. After each game, you will be put together with new participants to form a new market. This means that in each of the three games you interact with other participants.

After all games are finished, it will be randomly decided which of the three games will be paid out. You will receive your payoff after the experiment. You will also receive an additional 4.00 euros for participating in this experiment.

As a help we display a virtual calculator, with which you can calculate your profits in each round.

Comprehension Questions

Question 1: How many consumers are in the market who want to buy the product?

- 25
- 35
- 30
- 40

Question 2: What is the probability of playing another round after completing one?

- 95%
- 5%
- 50%

Question 3: You are firm A and choose a price of 2, firm B chooses a price of 10, firm C chooses a price of 9. What is your profit in ECU in this round?

Question 4: You are firm A and choose a price of 8, firm B chooses a price of 8, firm C chooses a price of 8. What is your profit in ECU in this round?

Question 5: You have a profit of 650 ECU, what is your profit in euros?

Question 6: What is the objective of the algorithm?

- Maximizing profits for all firms in a single round
- Maximizing total profits for all firms across all rounds
- Maximizing total profits for a single firm across all rounds
- Maximizing profits of a single firm in a single round

B.3 Post-experimental questionnaire

Gender: What is your gender?

- Male
- Female
- Diverse
- No specification

Experiments: In how many economic experiments have you (approximately) already participated?

GPA (School): What was the final grade of your last school diploma (1.0 - 4.0)?

Math Grade: What was your last math grade (1.0 - 6.0)?

Budget: How much money do you have available each month (after deducting fixed costs such as rent, insurance, etc.)?

Spending: How much money do you spend each month (after deducting fixed costs such as rent, insurance, etc.)?

Risk: Are you generally a person who is willing to take risks or do you try to avoid risks? Please indicate your answer on a scale of 0 to 10, where 0 means not willing to take risks at all and 10 means very willing to take risks.

Time: Compared to others, are you generally willing to give up something today in order to benefit from it in the future, or are you unwilling to do so compared to others? Please indicate your answer on a scale of 0 to 10, where 0 means not willing to give up at all and

10 means very willing to give up something.

Trust: As long as I am not convinced of the opposite, I always assume that other people only have the best in mind. How strongly do you agree with this statement? Please indicate your answer on a scale of 0 to 10, where 0 means not true at all and 10 means very true.

Neg. Rec.: Are you someone who is generally willing to punish unfair behavior, even if it comes at a cost for you, or are you unwilling to do so? Please indicate your answer on a scale of 0 to 10, where 0 means not willing to punish at all and 10 means very willing to punish.

Pos. Rec.: If someone does me a favor, I'm willing to return it. How strongly do you agree with this statement? Please indicate your answer on a scale of 0 to 10, where 0 means not true at all and 10 means very true.

Altruism: Imagine the following situation: You won 1,000 € in a prize competition. How much would you donate to charity in your current situation?

Appendix C Further results

C.1 Further analysis of the relation between the recommendation and individual prices

This section provides further details on how recommendations influence individual prices. As discussed in Section 3, there exists a positive and statistically significant influence of the recommendation on individual prices. However, participants do not follow the recommendations perfectly. When the algorithms recommend collusion, participants, on average, undercut the recommendation substantially while they choose higher prices in the punitive states of the algorithms.

To demonstrate the magnitude of these deviations, we define the indicator variable $\mathbf{1}_{\text{Collusive phase}}$, which is equal to one if the algorithm recommends collusion ($p_t^R = 10$), and zero if the algorithm recommends punishment in the current period ($p_t^R < 10$). We calculate the difference between the recommended price and the individual price ($p_t^R - p_t^i$) and regress it on $\mathbf{1}_{\text{Collusive phase}}$. The results from this regression are in Table C.1.

The regression indicates that participants undercut the recommendations in the collusive phase and chose substantially higher prices than the recommended ones in the punitive phase. To see this, consider model specification (1) in Table C.1. The constant measures the average difference between recommended and individual prices in the punitive phase. The coefficient of -1.77 indicates that, on average, participants choose a price higher than the recommendation. The sum of $\mathbf{1}_{\text{Collusive phase}}$ and the constant is the average difference in the collusive phase and it is approximately 3.55.

Note that the absolute difference between recommended and individual prices is greater in the collusive than in the punitive state. This difference across states is highly statistically significant in the first supergame ($p < 0.01$), statistically significant at the 10% level across all supergames, but becomes insignificant when considering only the last supergame (separate Wald tests based on the regressions from Table C.1). As such, adherence to the recommendation is initially greater when recommending punishment, but it becomes similar as participants learn about the game and the algorithms.

Additionally, the magnitude of these deviations differs by treatment (model specifications 3 and 4). During the punitive phase, participants overshoot more in the RecTheory treatment but undercut less in the collusive phase.[33]

[33] In RecSoft, the potential for upward deviations is inherently limited compared to RecTheory. While the recommended price in the punitive phase is always $p_t^R = 1$ in RecTheory, it ranges between $1 \leq p_t^R < 10$ in RecSoft. However, the treatment differences persist even when considering only rec-

Table C.1: Linear regression for the difference between recommendations and individual prices on a dummy variable indicating whether the recommendation is collusive ($p_t^R = 10$).

Dependent Variable:	$p_t^R - p_t^i$			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	-1.77***	-2.41***	-0.981***	-1.12***
	(0.402)	(0.644)	(0.148)	(0.272)
$\mathbf{1}_{\text{Collusive phase}}$	5.32***	5.40***	6.54***	5.77***
	(0.638)	(0.791)	(0.407)	(0.809)
RecTheory			-1.61**	-2.63**
			(0.654)	(1.02)
$\mathbf{1}_{\text{Collusive phase}}$ × RecTheory			-2.31**	-0.655
			(0.758)	(1.22)
Sub-sample	All	Super game 3	All	Super game 3
Fit statistics				
Observations	5,724	1,944	5,724	1,944
R^2	0.335	0.323	0.438	0.421
Adjusted R^2	0.334	0.322	0.437	0.420

Note: The coefficients are from a linear regression. The indicator variable $\mathbf{1}_{\text{Collusive phase}}$ equals 1 when the recommendation $p_t^R = 10$, and 0 otherwise. When $\mathbf{1}_{\text{Collusive phase}} = 0$, the constant reflects the average difference between recommended (p_t^R) and individual prices (p_t^i) in the punitive phase. The negative constant in Column 1 indicates that participants only partially follow punishment recommendations and price slightly above the recommendation. In the collusive phase ($\mathbf{1}_{\text{Collusive phase}} = 1$), the average difference is given by the sum of the constant and the coefficient on $\mathbf{1}_{\text{Collusive phase}}$, which is positive and shows that participants undercut the recommend on average in the collusive phase. This pattern is still present in the last supergame (Column 2). While the magnitude of the effect slightly differs, it is observed across both treatments (Column 3 and 4). Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; Clustered (Matching group) standard-errors in parentheses.

Overall, the average differences by treatment and state of the algorithms further support the evidence provided in Section 3 that participants only follow the recommendation partially. While they undercut the algorithms in the collusive phase, they choose, on average, higher prices than the recommended ones when the algorithm recommends punishment. As such, while participants factor the recommendation into their own pricing decisions, they do so imperfectly.

C.2 Randomization checks

Table C.2 provides the average outcome for different questionnaire measures for the main treatments. Furthermore, we test for differences in those measures across treatments using Kruskal-Wallis tests. A complete list of the different post-experimental questions we ask the participants is provided in Appendix B.3. There are few differences in the control variables across treatments. Only the budget participants have each month differs between treatments at the 5%-level. Importantly, controlling for these measures does not influence the main outcomes (see Table 2 and C.10). Thus, we conclude that randomization into treatments was largely successful.

C.3 Economic preferences and recommendations

In Section 3, we discuss the influence of negative reciprocity on market prices when participants receive a price recommendation (see Table 4). Here, we provide the same analysis for the other economic preferences measures. All measures have been normalized to be between zero and one. Furthermore, as the measures have been elicited on the individual level, we aggregated them by calculating the group specific mean.

Altruism and trust do not influence market prices. Interestingly, there is also no significant effect of positive reciprocity on market outcomes. In other words, while differences

ommendations at $p_t^R \in \{10, 1\}$ for RecSoft, suggesting that these differences are unlikely to be purely mechanical.

Table C.2: Individual characteristics by treatment

	Risk	**Time**	**Trust**	**Neg. Rec.**	**Pos. Rec**	**Altruism**	**Woman**
BASELINE	0.53	0.68	0.39	0.64	0.92	0.12	0.48
RECSOFT	0.49	0.70	0.41	0.52	0.88	0.14	0.50
RECTHEORY	0.54	0.74	0.49	0.62	0.84	0.10	0.54
P-values	0.73	0.35	0.18	0.09	0.19	0.84	0.84

	Experiments	**Math Grade**	**GPA (School)**	**Budget**	**Spending**
BASELINE	7.24	1.99	1.99	414.98	300.15
RECSOFT	11.52	2.47	2.31	378.61	275.63
RECTHEORY	10.69	2.12	2.05	523.89	339.87
P-values	0.38	0.07	0.05	0.04	0.39

Note: The preferences measures are based on the questions by Falk et al. (2023) and scaled between zero and one. The p-values are based on Kruskal-Wallis-tests.

in negative reciprocity lead to vastly different prices within and between treatment, it is not the case for positive reciprocity.

Furthermore, differences in time preferences amongst sellers lead to distinct market outcomes (see Table C.3 where a higher level of TIME corresponds to more patience). In BASELINE and RECSOFT, the prices are more collusive for markets with more patient participants. This makes intuitive sense. For collusion to be sustainable, participants must value the long-run profits more than any short-term gains from possible deviations.[34] This is arguably the case for groups of sellers who are more patient. For RECTHEORY, on the other hand, market prices are higher than in BASELINE if market participants are impatient. In other words, the recommendations foster collusion in situations where participants tend to deviate more due to their lack of patience. As the effect of TIME is negative in this treatment, the effect wears off for more patient participants, and market prices become similar to BASELINE for values of TIME close to one. For large values of TIME,

[34]As noted by Davis et al. (2016), one needs to assume that subjects receive utility from obtaining ECU after each period rather than from receiving the money at the end of the experiment. Kim (2023) uses delayed payoffs to induce actual time preferences in the strategically similar iterated prisoners dilemma and finds a positive association between cooperation and patients.

the recommendation even has a negative effect on market prices compared to BASELINE.[35] Evidently, the recommendations lead to lower prices if sellers are particularly patient. It is possible that participants who are particularly patient would not have punished in the first place without the recommendation. Small deviations may lead to harsher punishment than usual.

However, it is essential to note that this effect wears off after learning (Model (4) of Table C.3). In the last supergame, the effects become statistically insignificant. Patience appears only relevant in the initial rounds of the game when participants do not yet fully understand the recommendation algorithm.

[35] The average marginal effect of RECTHEORY is negative and significant at the 5% level for TIME being equal to the maximum value of one. See Table C.9 in the online appendix.

Table C.3: Market price explained by time preferences and treatments

Dependent Variable:	Market price			
Model:	(1)	(2)	(3)	(4)
Variables				
TIME	4.57*	9.06**	9.06**	2.75
	(2.22)	(3.56)	(3.57)	(5.45)
RECTHEORY		8.25*	8.25*	1.78
		(4.18)	(4.20)	(5.22)
RECSOFT		0.154	0.154	-6.44
		(3.47)	(3.48)	(5.35)
TIME × RECTHEORY		-11.2**	-11.2**	-1.95
		(5.21)	(5.24)	(7.40)
TIME × RECSOFT		-2.65	-2.65	7.14
		(5.01)	(5.03)	(7.90)
Sub-sample:	All	All	All	Supergame 3
Fixed-effects				
Round			Yes	Yes
Supergame			Yes	Yes
Fit statistics				
Observations	2,862	2,862	2,862	972
R^2	0.024	0.099	0.136	0.092
Within R^2			0.103	0.075

Note: The coefficients are from a linear regression. Model specifications without fixed effects are estimated with a constant. For the fixed effects regression, we include dummies for each of the rounds and supergames. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; Clustered (Matching group) standard errors in parentheses.

Table C.4: Market price explained by altruism and treatments

Dependent Variable:	Market price			
Model:	(1)	(2)	(3)	(4)
Variables				
Altruism	-1.34	0.191	0.191	-5.91
	(3.34)	(8.56)	(8.61)	(9.57)
RecTheory		-0.209	-0.209	-0.352
		(1.65)	(1.65)	(2.54)
RecSoft		-1.10	-1.10	-1.41
		(1.14)	(1.14)	(1.68)
Altruism × RecTheory		6.43	6.43	7.26
		(10.9)	(10.9)	(17.4)
Altruism × RecSoft		-3.14	-3.14	1.15
		(8.65)	(8.70)	(10.1)
Sub-sample:	All	All	All	Supergame 3
Fixed-effects				
Round			Yes	Yes
Supergame			Yes	Yes
Fit statistics				
Observations	2,862	2,862	2,862	972
R^2	0.001	0.061	0.098	0.071
Within R^2			0.064	0.054

Note: The coefficients are from a linear regression. Model specifications without fixed effects are estimated with a constant. For the fixed effects regression, we include dummies for each of the rounds and supergames. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; Clustered (Matching group) standard errors in parentheses.

Table C.5: Market price explained by positive reciprocity and treatments

Dependent Variable:	Market price			
Model:	(1)	(2)	(3)	(4)
Variables				
Pos. Rec.	3.41	6.26	6.26	3.58
	(3.62)	(5.53)	(5.56)	(6.62)
RecTheory		3.82	3.82	5.74
		(5.54)	(5.57)	(7.09)
RecSoft		-3.13	-3.13	-1.98
		(7.41)	(7.44)	(13.6)
Pos. Rec. × RecTheory		-3.43	-3.43	-5.89
		(6.12)	(6.15)	(8.27)
Pos. Rec. × RecSoft		2.07	2.07	0.847
		(8.31)	(8.36)	(15.4)
Sub-sample:	All	All	All	Supergame 3
Fixed-effects				
Round			Yes	Yes
Supergame			Yes	Yes
Fit statistics				
Observations	2,862	2,862	2,862	972
R^2	0.009	0.070	0.106	0.065
Within R^2			0.072	0.048

Note: The coefficients are from a linear regression. Model specifications without fixed effects are estimated with a constant. For the fixed effects regression, we include dummies for each of the rounds and supergames. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; Clustered (Matching group) standard errors in parentheses.

Table C.6: Market price explained by risk preferences and treatments

Dependent Variable:	Market price			
Model:	(1)	(2)	(3)	(4)
Variables				
Risk	2.65	4.45*	4.45*	-1.66
	(1.55)	(2.16)	(2.17)	(5.67)
RecTheory		4.21	4.21	-2.17
		(3.03)	(3.05)	(4.88)
RecSoft		-0.654	-0.654	-4.25
		(1.56)	(1.57)	(3.88)
Risk × RecTheory		-7.07	-7.07	4.98
		(4.81)	(4.83)	(9.17)
Risk × RecSoft		-1.45	-1.45	5.72
		(3.13)	(3.15)	(7.52)
Sub-sample:	All	All	All	Supergame 3
Fixed-effects				
Round			Yes	Yes
Supergame			Yes	Yes
Fit statistics				
Observations	2,862	2,862	2,862	972
R^2	0.010	0.069	0.106	0.077
Within R^2			0.072	0.060

Note: The coefficients are from a linear regression. Model specifications without fixed effects are estimated with a constant. For the fixed effects regression, we include dummies for each of the rounds and supergames. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; Clustered (Matching group) standard errors in parentheses.

Table C.7: Market price explained by trust preferences and treatments

Dependent Variable:	Market price			
Model:	(1)	(2)	(3)	(4)
Variables				
Trust	1.20	-1.01	-1.01	-0.454
	(1.73)	(4.13)	(4.15)	(6.39)
RecTheory		-0.835	-0.835	-0.203
		(3.06)	(3.07)	(3.41)
RecSoft		-2.16	-2.16	-1.98
		(1.77)	(1.78)	(2.38)
Trust × RecTheory		2.79	2.79	1.51
		(5.58)	(5.61)	(7.34)
Trust × RecSoft		1.58	1.58	1.54
		(4.38)	(4.40)	(7.40)
Sub-sample:	All	All	All	Supergame 3
Fixed-effects				
Round			Yes	Yes
Supergame			Yes	Yes
Fit statistics				
Observations	2,862	2,862	2,862	972
R^2	0.003	0.055	0.092	0.061
Within R^2			0.057	0.044

Note: The coefficients are from a linear regression. Model specifications without fixed effects are estimated with a constant. For the fixed effects regression, we include dummies for each of the rounds and supergames. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; Clustered (Matching group) standard errors in parentheses.

Table C.8: Treatment effects conditionally on Neg. Rec. being at the minimum and maximum value based on Model 2 of Table 4

Treatment	Neg. Rec.	AME	SE	z	p	lower	upper
RecSoft	0	-5.51	1.22	-4.53	0.00	-7.90	-3.13
RecSoft	1	1.34	0.94	1.44	0.15	-0.49	3.18
RecTheory	0	-2.44	0.94	-2.61	0.01	-4.27	-0.61
RecTheory	1	2.10	1.56	1.35	0.18	-0.96	5.15

Table C.9: Treatment effects conditionally on TIME being at the minimum and maximum value based on Model 2 of Table C.3

Treatment	TIME	AME	SE	z	p	lower	upper
RECSOFT	0	0.15	3.47	0.04	0.96	-6.64	6.95
RECSOFT	1	-2.50	1.64	-1.53	0.13	-5.71	0.71
RECTHEORY	0	8.25	4.18	1.97	0.05	0.05	16.45
RECTHEORY	1	-2.99	1.46	-2.05	0.04	-5.86	-0.13

C.4 Additional control treatments

We consider two additional control treatments. We consider for both only 36 subjects, which yields considerably less power than in the main treatments. As a result, we report the results only here in the Appendix. In RECSTATIC, participants receive a static price recommendation at the monopoly in each period. Also, after deviations from the recommended price, the algorithm recommends the monopoly price, and there is no punishment mechanism. Furthermore, we consider the RECNASH algorithms. Similar to RECTHEORY, the stage game Nash equilibrium is recommended in the subsequent period after any deviation from the monopoly price. Yet, the algorithm reverts back to the monopoly after one punishment round and is thus, in contrast to RECTHEORY, not incentive compatible. The results are provided in Figure C.1. Both treatments yield similar market prices as in BASELINE and RECTHEORY. It highlights that algorithms without any punishment mechanism or a shorter punishment length also do not increase market prices.

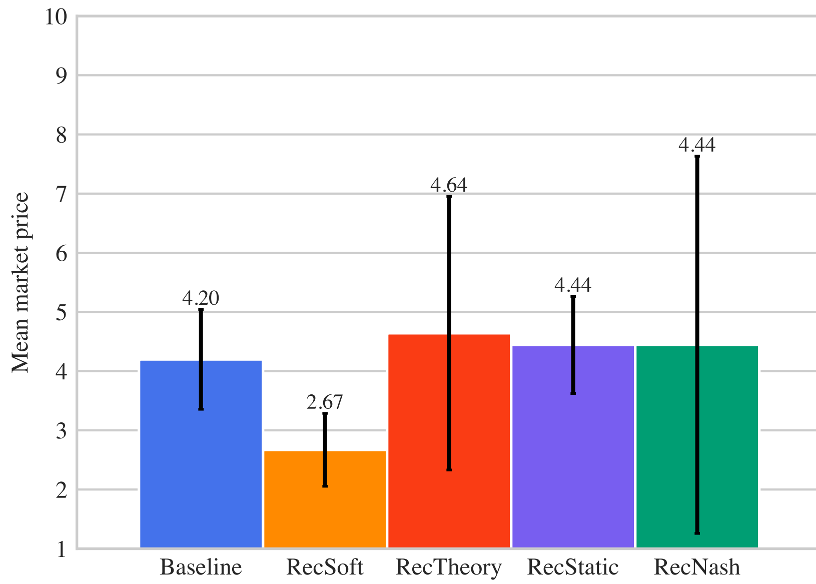

Figure C.1: Market price for all treatments. The error bars represent 95% confidence intervals.

C.5 Further figures and tables

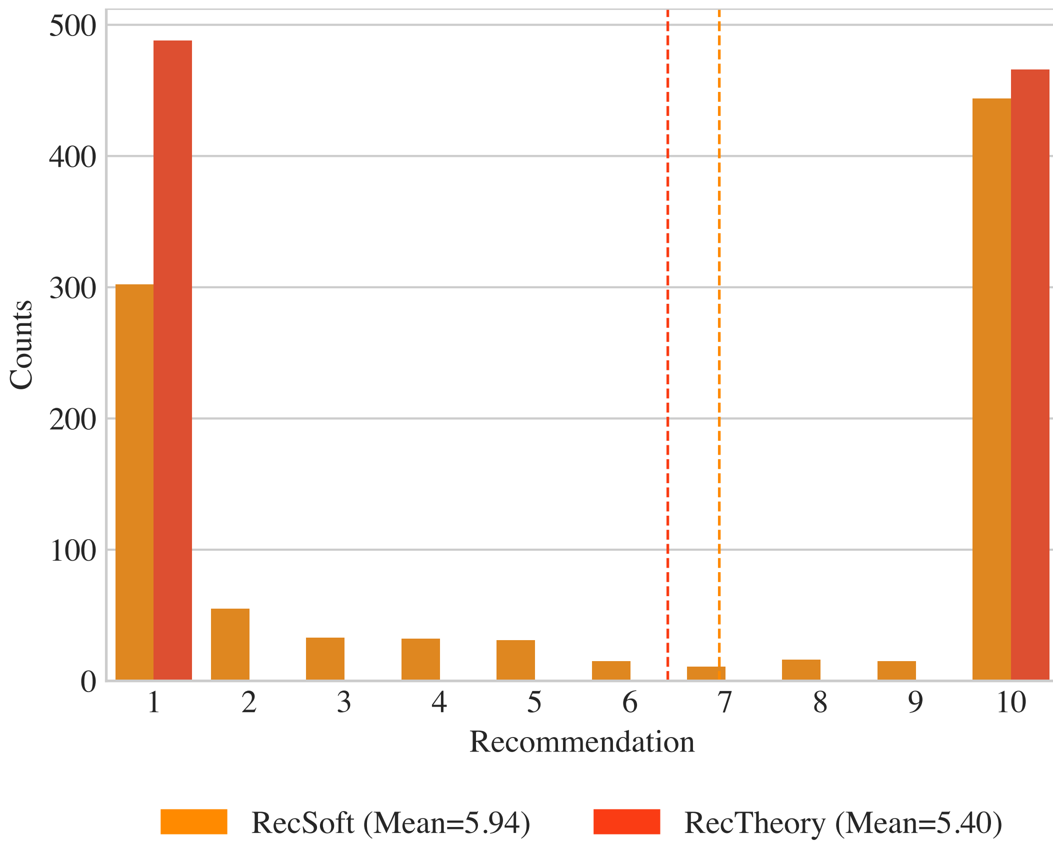

Figure C.2: Count plot for the different price recommendations in RecTheory and RecSoft across all markets and rounds. The vertical dashed lines show the mean recommendation in the respective treatment.

Table C.10: Linear regression for the treatment effects relative to BASELINE.

Dependent Variable:	Market price		
Model:	(1)	(2)	(3)
Variables			
RECSOFT	-1.53***	-1.53***	-1.45**
	(0.382)	(0.384)	(0.530)
RECTHEORY	0.442	0.442	0.823
	(0.899)	(0.904)	(1.00)
Further controls:			Yes
Fixed-effects			
Round		Yes	Yes
Supergame		Yes	Yes
Fit statistics			
Observations	2,862	2,862	2,862
R^2	0.052	0.089	0.149
Within R^2		0.054	0.117

Note: The coefficients are from a linear regression. Model specifications without fixed effects are estimated with a constant. For the fixed effects regression, we include dummies for each of the rounds and supergames. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; Clustered (Matching group) standard errors in parentheses.

Table C.11: Linear regression with the treatment effects by supergame.

Dependent Variable:		Market price	
	(Supergame 1)	(Supergame 2)	(Supergame 3)
Model:	(1)	(2)	(3)
Variables			
RecSoft	-1.63**	-1.56*	-1.36*
	(0.572)	(0.881)	(0.740)
RecTheory	0.539	-0.007	0.497
	(0.990)	(1.27)	(1.26)
Fixed-effects			
Round	Yes	Yes	Yes
Fit statistics			
Observations	1,458	432	972
R^2	0.087	0.041	0.059
Within R^2	0.073	0.038	0.042

Note: The coefficients are from a linear regression. For the fixed effects regression, we include dummies for each of the rounds and supergames. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; Clustered (Matching group) standard errors in parentheses.

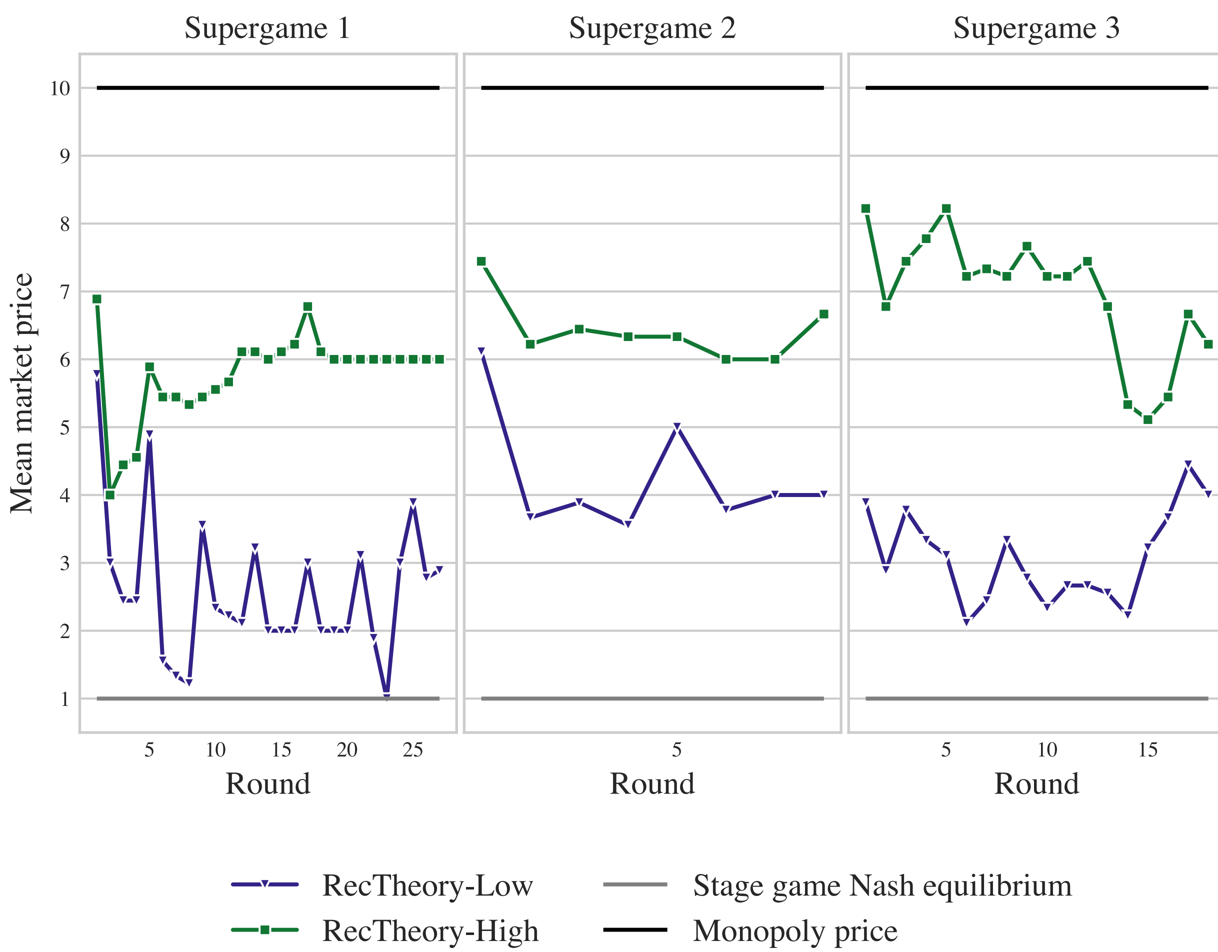

Figure C.3: Market price in RecTheory for matching groups above (High) and below (Low) the median market price by supergame and round.

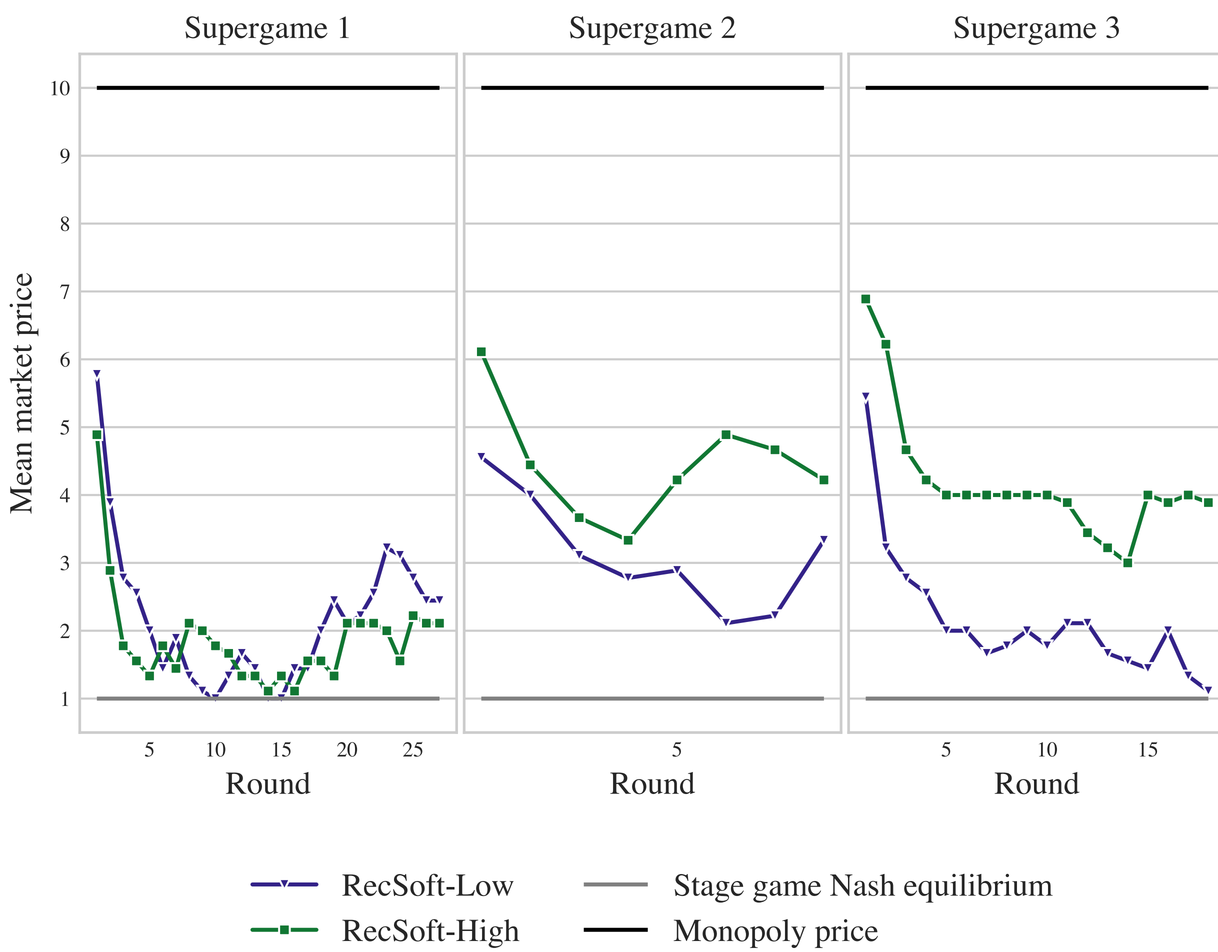

Figure C.4: Market price in RecSoft for matching groups above (High) and below (Low) the median market price by supergame and round.

Appendix D Incentives of intermediaries to provide collusive recommendations

In this section, we theoretically argue that platforms like Airbnb, Booking, and eBay, which provide price recommendations to their sellers, may have an incentive to foster collusion in the downstream market. This analysis substantiates our claim regarding their incentives and justifies their use as a motivating example for possible collusive price recommendation providers.[36] Previously, we abstracted from the incentives of the algorithm developer because it simplifies theoretical predictions and allows for a straightforward experimental implementation. Here, we instead focus on the contracting between a platform and different sellers to analyze how the optimal price level depends on commission rates and costs. We depart from the market environment outlined earlier to accommodate strategic considerations that a platform may have. We demonstrate that a platform can benefit from collusive recommendations even if it possesses the bargaining power to determine the commission rate.

In general, it is conceivable that the incentives of the provider and the sellers are aligned with respect to the price level. Even if the recommendation provider's income does not directly depend on the sellers' prices, using algorithmic pricing software may increase the sellers' profits and thus their willingness to pay for working with such a provider. Intermediary oftentimes charge sellers a commission that is a fraction of the sales price. Intermediaries often use such a revenue-based compensation, for instance many online platforms such as Amazon, eBay and AirBnB.[37] Such intermediaries may thus benefit from higher prices if there is seller competition for a given commission rate. However, an

[36]Note that platforms are just one example of a third party that may have incentives to foster collusion in the downstream market with price recommendations. For instance, third-party developers of pricing algorithms may also be incentivized to foster collusion, as argued by Ezrachi and Stucke (2017) and Harrington (2022).

[37]Although these platforms although provide price recommendations, by mentioning them we do not mean to imply that they provide collusive price recommendations.

obvious question is why intermediaries need collusive recommendations and cannot just increase to commission rate in order to increase the sales prices and the resulting revenues.

High commission rates versus collusive recommendations. We demonstrate that a monopoly platform can achieve higher profits through collusive price recommendations for sellers than when just charging a high commission rate to the sellers.[38] This comparison is relevant as many online sales platforms use commission rates, and a natural question is whether a sales platform needs recommendations to achieve the desired seller price level. This analysis adds to the developing literature on seller collusion on online platforms, which focuses on settings where commission rates are sufficient for achieving high prices (Schlütter, 2022; Teh, 2022).[39] Teh (2022) has a related finding whereby it can be optimal for a platform to increase the seller margins through platform design, such as entry regulations, if that is value-generating. He does, however, not consider seller collusion and uses a different modeling approach.

There are $n \geq 2$ symmetric sellers who sell products with marginal costs c. Each seller i makes a profit of

$$\pi_i = (p_i - r \cdot p_i - c)q_i(p_i, p_{-i})$$

when selling on the platform, which charges a commission rate of r. Demand q_i is differentiable and has the usual properties. In particular, it decreases in the own price p_i and increases the competitors' price(s) p_{-i}.[40] A seller's (opportunity) costs of being active on

[38]We focus on a monopoly platform as this is common in many markets. Many larger platforms possess market power due to positive network effects, which is acknowledged by competition authorities (Bundeskartellamt, 2016). Even if there is competition among platforms, sellers often single-home and do not use multiple competing platforms simultaneously (Karle et al., 2020).

[39]Schlütter (2022) primarily studies price parity clauses in a market where sellers can alternatively sell only via their direct sales channel.

[40]Imperfect price competition where the sellers can earn positive margins may arise for various reasons, including product differentiation, but also uncertainty about the competitors' costs and other frictions. Positive profit margins are also observed in our experiment, absent any collusive recommendations, although the products are not differentiated.

the platform are $I \geq 0$, such that the seller participates if and only if

$$\pi_i \geq I. \tag{1}$$

We focus on situations where the platform wants to ensure that all sellers participate, so that condition (1) holds for all i.

A seller's first order condition concerning its sales price is

$$(p_i - r \cdot p_i - c)\frac{\partial q_i(p_i, p_{-i})}{\partial p_i} + (1-r)q_i(p_i, p_{-i}) = 0$$

and can be written as

$$(p_i - \frac{c}{(1-r)})\frac{\partial q_i(p_i, p_{-i})}{\partial p_i} + q_i(p_i, p_{-i}) = 0. \tag{2}$$

Let $p^*(r, c)$ denote the symmetric Nash equilibrium price that solves the above equation when all n sellers compete.

At the competitive sales prices, the platform makes a profit of

$$\Pi(r) = r \cdot p^*(r, c) \cdot n \cdot q_i(p^*, p^*).$$

Platform profit maximization when sellers compete. For $c = 0$ the platform cannot influence the price level with r as it disappears in the first order condition (2).

For $c > 0$ the implicit function theorem on the first order condition (2) for the case of symmetric sales prices $p_i = p_{-i} = p^*$ yields $\partial p^*/\partial r > 0$ under the standard assumptions of a strictly concave seller profit π_i in p_i and decreasing demand ($\partial q_i/\partial p_i < 0$). The platform can thus raise the price level as long as selling remains profitable for the sellers.

Suppose that the sellers make lower profits if their common input costs increase. This is consistent with economic intuition and holds under standard demand assumptions. A sufficient condition for this is that the sellers' profit margin decreases as the costs increase: $\partial p^*/\partial k < 1$ with $k = c/(1-r)$. This is, for instance, the case with linear demand.

For illustration, suppose that $r = 0$ and that the resulting seller profits equal zero:

$$(p^* - c)q_i(p^*, p^*) - I = 0.$$

It is thus not feasible for the platform to charge a positive commission rate as the sellers would not break even. This argument generalizes to the case where break-even occurs at a positive commission rate that yields a price level $\hat{p}$, which is below the level that maximizes the producer surplus. The platform is then restricted in setting of the commission rate, which cannot maximize the producer surplus.[41]

Conversely, it might be that the platform achieves the producer surplus maximizing price at a commission rate where the sellers make positive profits ($\pi_i > I$). This occurs if I is small enough. The platform then leaves more profits than necessary for the sellers to participate. It would thus be optimal for the platform to charge a higher commission rate while keeping the sales prices constant. This relates to the problem of double marginalization.

Platform profit maximization when sellers collude. For simplicity, assume that the platform can implement any price level p through recommendations. The platform can thus implement a price p and set r such that

$$(p \cdot (1 - r) - c) \cdot q_i(p, p) = I.$$

[41]Fixed fees might solve the problem. However, large fixed fees, and in particular transfers to sellers, might not work in practice. For instance, they might incentivize people to register as sellers just to obtain the transfers. Indeed, large fixed fees are not used on many online sales platforms.

The platform can thus implement the producer surplus maximizing price

$$p^M = \arg\max_p \, (p - c) \cdot \sum_{i=1}^{n} q_i(p, p) - n \cdot I$$

and extract through r all seller revenues up to $I + c \cdot q_i(p^M, q^M)$ per seller.

In summary, this analysis shows that a platform can benefit from prices recommendations even if it can change its commission rates for one of the following reasons:

- The sellers have (opportunity) costs of selling on the platform, such that a high commission rate is not acceptable but would be necessary for achieving high sales prices of competing sellers.
- The platform charges a commission rate, and the sellers do not have marginal costs other than the commission payment, so the commission rate does not affect the sellers' pricing.
- A high commission rate is optimal to extract the seller's profits but yields too high sales prices (excessive double marginalization). In this case, recommendations below the competitive level can be optimal.
- In addition to the above formal analysis, a platform might desire to charge the same commission rate across different markets to maintain a simple, transparent policy, albeit different seller price levels are optimal.