DICE

DISCUSSION PAPER

NO 392

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October 2022

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Universität Düsseldorf

IMPRINT

DICE DISCUSSION PAPER

Published by:
Heinrich-Heine-University Düsseldorf,
Düsseldorf Institute for Competition Economics (DICE),
Universitätsstraße 1, 40225 Düsseldorf, Germany
www.dice.hhu.de

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ISSN 2190-9938 (online) / ISBN 978-3-86304-391-9

Human-Algorithm Interaction: Algorithmic Pricing in Hybrid Laboratory Markets

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Abstract: This paper investigates pricing in laboratory markets when human players interact with an algorithm. We compare the degree of competition when exclusively humans interact to the case of one firm delegating its decisions to an algorithm, an n-player generalization of tit-for-tat. We further vary whether participants know about the presence of the algorithm. When one of three firms in a market is an algorithm, we observe significantly higher prices compared to human-only markets. Firms employing an algorithm earn significantly less profit than their rivals. (Un)certainty about the actual presence of an algorithm does not significantly affect collusion, although humans do seem to perceive algorithms as more disruptive.

JEL classification: C90, L41.

Keywords: algorithms, collusion, human-computer interaction, laboratory experiments

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Acknowledgements. We are grateful to the editor, David Levine, an associate editor, and two referees for helpful comments. We further thank Christoph Engel, Bernhard Ganglmair, Joe Harrington, Timo Klein, Marcel Schubert, Frederike Zufall, as well as seminar participants at ALEA 2021, Bayreuth University, CLEEN Workshop 2021, Competition and Regulation Day Mannheim 2020, Crossroads of Law and Economics Workshop Rotterdam 2022, DICE Winter School 2020, EARIE 2021, IMPRS Uncertainty Thesis Workshop 2019, MPI Bonn Lab Meeting, and Third Open Antitrust Doctoral Seminar 2019 for useful suggestions that improved the paper.

1 Introduction

Algorithms are increasingly taking over price decisions on behalf of the firms that employ them. Whereas pricing algorithms are also used in more traditional brick-and-mortar retailing, for example in supermarkets[1] or gasoline stations,[2] the strongly growing e-commerce sector[3] adds to their rapid dissemination. In its "E-commerce Sector Inquiry", the EU Commission (2017) reports that a majority of online firms track the prices of competitors and two-thirds of these use algorithmic pricing software. So, algorithms are on the rise.

While algorithms may benefit consumers,[4] a major concern is that they could weaken competition and make supracompetitive prices more likely. The challenges associated with algorithmic pricing, in particular the risk of tacit collusion, are widely discussed (Ezrachi and Stucke, 2016, 2017; Harrington, 2018, 2020; Haucap, 2021; Mehra, 2016; Monopolkommission, 2018; OECD, 2017; Oxera, 2017) and seem to be high on the agenda of competition authorities around the world (British Competition and Markets Authority, 2018, 2021; Bundeskartellamt and Autorité de la Concurrence, 2019; Competition Bureau Canada, 2018).

Empirical research suggests that the pricing algorithms currently primarily used in digital markets follow relatively simple pricing strategies (British Competition and Markets Authority, 2018; Monopolkommission, 2018; Musolff, 2021; Wieting and Sapi, 2021). Static algorithms that follow a manageable number of simple pricing rules appear to be common. The lack of sophistication may actually increase the risk of tacit collusion. Supracompetitive prices could become more likely by having these algorithms induce firms to behave in a predictable and consistent man-

[1] See "Surge Pricing Comes To The Supermarket", *The Guardian*, 4 June, 2017, available at: https://bit.ly/3mf9IQp (last accessed on 22 October, 2022).

[2] See Assad et al. (2020) and "Why Do Gas Station Prices Constantly Change? Blame the Algorithms", *Wall Street Journal*, 8 May, 2017, available at: https://on.wsj.com/3vRCRo3 (last accessed on 22 October, 2022).

[3] In 2021, 74% of internet users in the EU ordered goods or services online. See 2021 Eurostat Community Survey on ICT usage in households and by individuals, available at: https://bit.ly/3biBEga (last accessed on 22 October, 2022).

[4] Algorithms are ideally suited to deal with the wealth of data available online on competitors and customers. Pricing algorithms can adjust prices, enable consistent pricing strategies, and react immediately to any changes in the market environment (OECD, 2017). Such efficiency gains may ultimately be good for consumers.

ner (British Competition and Markets Authority, 2018; Wieting and Sapi, 2021).[5] When interacting with humans, such algorithms could facilitate collusion. Algorithms act in a more systematic and reliable way than humans. Delegating pricing to such an algorithm reduces the strategy sets and can thus simplify the coordination via the market (Byrne and De Roos, 2019; Kastius and Schlosser, 2021; Musolff, 2021).[6]

Our paper analyzes these issues in "hybrid" markets where human players and algorithms interact. We study the price level in experimental oligopolies, where only humans interact, comparing this to the case where one firm in the market delegates its decisions to a simple algorithm. Our research question is whether the presence of an algorithm leads to an increase in prices.

Hitherto, surprisingly few laboratory experiments have studied cooperation when one or more players are computerized, and only one compares human-computer to all-human interaction. Roth and Murnighan (1978) and Murnighan and Roth (1983) analyze two-player prisoner's dilemmas when subjects know they face an algorithmic opponent.[7] Duffy and Xie (2016) have single humans play against $n-1$ grim trigger players, and the authors vary n. The participants of the experiments in Duersch et al. (2009) play against various learning-algorithms in a Cournot-setting, and recently Duffy et al. (2021) let participants play two-player prisoner's dilemma supergames against a grim-trigger algorithm. In Duffy and Xie (2016) and Duffy et al. (2021), subjects know the strategy the algorithm plays. This is

[5] Wieting and Sapi (2021) analyze the e-commerce platform *Bol.com* (the largest online marketplace in Belgium and the Netherlands) and identify pricing software that was foremost "relatively unsophisticated" and "consist of a finite set of if-then statements." Wieting and Sapi (2021) conclude that "[a] secret to successful collusion may lie in managers' ability to commit to simple strategies".

[6] Byrne and De Roos (2019) study a data set from the retail gasoline industry in an Australian city. Their findings suggest that firms "may adopt simple pricing structures, even in the presence of perfect price monitoring, because they are easy to experiment with and communicate to rivals". Musolff (2021) employs data on the pricing decisions made by third-party sellers on the e-commerce platform Amazon and finds that "delegation of pricing to simple algorithms can facilitate tacit collusion by reducing the set of available strategies". Kastius and Schlosser (2021) show that a simple pricing rule can force a self-learning reinforcement algorithm to collude by plainly pricing competitively until the algorithm "agrees" to charge a high price.

[7] Roth and Murnighan (1978) and Murnighan and Roth (1983) are known to be the first to study "infinitely" repeated games in the lab by imposing a random move that determines the end of a supergame.

not the case in Roth and Murnighan (1978), Murnighan and Roth (1983), and Duersch et al. (2009). The five studies have in common that they do not have comparison treatments when the opponents are human. Finally, the recent computer-science paper by Crandall et al. (2018) is an experiment on human-machine cooperation in stochastic games. The paper studies how autonomous machines learn to establish cooperative relationships with people and other machines in repeated two-player interactions. Although the level of human-machine cooperation is not higher than the level of human-only cooperation, Crandall et al. (2018) demonstrate human-machine cooperation is achievable using relatively simple reinforcement algorithms.

A second novelty of our study is that we explore the role of human beliefs about algorithms. We vary (in a non-deceptive manner) whether or not participants know about the presence of the algorithm. Do participants behave differently when they are aware they are facing an algorithm? This may indeed be the case: Studies on "algorithm aversion" show that people avoid algorithmic advice even though the algorithm is superior to humans (Dietvorst and Bharti, 2020; Dietvorst et al., 2016, 2015). Furthermore, Farjam and Kirchkamp (2018) show in a laboratory asset market that humans trade differently if they expect algorithmic traders. As a possible explanation, they suggest that human traders perceive the algorithmic traders as behaving more rationally. De Melo et al. (2015) find that people tend to make different decisions depending on whether they are facing a human or a computer algorithm.[8] Thus, it seems warranted to test whether expectations about algorithms influence the behavior of participants.

To analyze these research questions, we opted for a rather simple and transparent experimental design. In three-firm markets, participants have two actions (high price, low price) available, so they play a three-player prisoner's dilemma.[9] As mentioned, one of the human participants may

[8]The authors had people participate in experiments with virtual humans controlled by either computer algorithms (agents) or humans (avatars), and show that having avatars involved in decision making compared to agents has an impact on people's decision making, such as their willingness to cooperate. For related findings on differences in decision making, see Dijkstra et al. (1998), Weibel et al. (2008), Krach et al. (2008), Lee (2018) and Rilling et al. (2004).

[9]While collusion is less likely in markets with more than two competitors, the reduced action set may promote tacit collusion (Gangadharan and Nikiforakis, 2009). For a recent survey on indefinitely repeated prisoner's dilemma games, see Dal Bó and Fréchette (2018). Mengel (2018) surveys one-shot and finitely repeated prisoner's dilemmas.

be replaced by an algorithm. The algorithm we use is a multiplayer generalization of tit-for-tat (Axelrod, 1984; Hilbe et al., 2015). It begins by cooperating, but subsequently adapts to the level of cooperation in the market. Tit-for-tat is cooperative, so when matched with other cooperative strategies, it achieves collusive payoffs. It is also forgiving in that it can return to cooperation after an accidental deviation and it avoids the exploitation by defectors. That said, our algorithm is not ferociously committed to cooperating and thus seems suitable to study human-algorithm interaction meaningfully.

We choose the specific algorithm in order to give cooperation a reasonably good chance. Our algorithm is comparable to the aforementioned, relatively simple, programs that appear to be used in online markets (British Competition and Markets Authority, 2018; Monopolkommission, 2018; Musolff, 2021; Wieting and Sapi, 2021). Another strand of literature investigates the collusive potential of rather complex self-learning reinforcement algorithms. Whereas the learning mechanisms (often Q-learning) behind these algorithms are hugely complicated, the strategies they produce are memory-one — a property they share with our algorithm.[10]

Experiments with three firms seem promising when it comes to identifying collusive effects in that duopolies can be collusive, whereas markets with four or more firms are usually not; see Engel (2015), Fonseca and Normann (2012), Huck et al. (2004), and Potters and Suetens (2013). The evidence on cooperation in three-player groups is somewhat inconclusive (and hence a good starting point for us). While Horstmann et al. (2018) do find some collusion in three-firm oligopolies with differentiated goods, Freitag et al. (2020) do not find any supracompetitive outcomes in a multimarket context benign to collusion. Marwell and Schmitt (1972) had already reported that three-person prisoner's dilemmas are substantially less coop-

[10]This literature shows that self-learning algorithms are able learn to play repeated-game strategies that maximize joint profits without explicitly being instructed to do so (Calvano et al., 2020, 2021; Klein, 2021). After an off-the-job learning phase, the algorithms execute a memory-one pricing strategy on the market. When two such algorithms interact with each other, striking levels of collusion occur. In their online appendix, (Calvano et al., 2020) briefly report on memory-two algorithms. As the state space disproportionally increases with a two-period memory, these algorithms perform less collusively. Dal Bó and Fréchette (2019) and Romero and Rosokha (2019) recently found that the strategies of human subjects in lab experiments are often memory-one. See also Fudenberg and Karreskog (2020).

erative than two-player experiments. Roux and Thöni (2015) demonstrate that larger oligopolies become collusive only when targeted punishments are available.

Our findings are as follows. The markets involving an algorithmic player are significantly more collusive than human-only triopolies. While this higher level of collusion raises profits for all firms in the industry, it turns out that those firms that employ the algorithm earn significantly less profit than their rivals. Knowing or not knowing about the presence does not affect competition significantly. Interestingly, however, humans seem to link cooperation to human behavior and not an algorithm.

2 Experimental Design

The stage game underlying the experiment is a three-player prisoner's dilemma framed as a market interaction. Players choose a high price or a low price, so the action set for all players is $\{p_{high}, p_{low}\}$. The payoffs are derived from a Bertrand oligopoly model with inelastic demand and constant marginal costs of production.[11] For actions $p_{high} = 100$ and $p_{low} = 60$, the payoffs in Table 1 (which is similar to the one used in the experiment) result.

Own price	Other firms' prices: p_{high}, p_{high}	p_{high}, p_{low}	p_{low}, p_{low}
p_{high}	$\pi^c = 800$	$\pi^s = 0$	$\pi^s = 0$
p_{low}	$\pi^d = 1{,}440$	$\pi^f = 720$	$\pi^n = 480$

Table 1: Payoff table.

We run four treatments in a 2×2 design. We vary treatments with and without algorithms and treatments with and without information on the presence of the algorithm. See Table 2.

[11] Suppose there are $m = 24$ consumers who demand one unit of the good up to a reservation price of 100. Each player can supply all consumers at production costs of zero. The player who charges the lowest price serves all consumers; if several players

Three humans	Two humans, one algorithm
Human_Uncertain	Algorithm_Uncertain
Human_Certain	Algorithm_Certain

Table 2: Treatment design.

In all experiments, groups of three participants constitute one market. In the treatments labeled "Human_", there are three human players. In the treatments labeled "Algorithm_", there are two human players and one algorithm. In treatments involving an algorithm, the computer decides on behalf of one firm. That firm is nevertheless represented by an experimental subject, but he or she is inactive and merely obtains the payoff earned by the algorithm.

The second treatment dimension indicates whether the participants know the composition of the market.[12] In the treatments labeled "_Certain", participants know from the instructions (reproduced in the Additional Material[13]) whether or not an algorithm is present. In the "_Uncertain" treatments, the participants do not know if they are part of the Human_Uncertain or the Algorithm_Uncertain treatment, so they do not know whether an algorithm is present. They are merely told that, with a probability of 50%, one of the three subjects' decisions is taken by an algorithm. The algorithm is either present or not present throughout the experiment, in all rounds and supergames. We conducted the same number of sessions in both treatments. Thus, consistent with the instructions, there was a 50% chance that the participants were in the Algorithm_Uncertain treatment.

The algorithm is programmed to play *proportional tit-for-tat*, or $pTFT$ (Hilbe et al., 2015). It is an n-player generalization of tit-for-tat (Axelrod, 1984): Let t be the index for time. The algorithm begins by cooperating in the first period ($t = 0$) and later cooperates proportionally to the number

charge the lowest price, they split the profit equally.

[12]Regarding this point, our design is similar to the one in Farjam and Kirchkamp (2018).

[13]Available in our Working Paper Normann and Sternberg (2022).

of cooperators in the previous period. Accordingly, $pTFT$ chooses the high price with the following probabilities

$$prob.(p = p_{high}) = \begin{cases} 1 \text{ if } & t = 0 \\ \frac{j}{n-1} \text{ if } & t > 0 \end{cases}$$

where n is the number of players including the algorithm player and $j \in \{0, 1, 2, ..., n-1\}$ is the number of rival players who chose p_{high} in the previous period. Subjects are not told how the algorithm is programmed. Nor are they told the algorithm's purpose.

The treatments are implemented as repeated games, and all treatments have three supergames.[14] The subjects stay in the same market throughout the periods of the supergames. When a new supergame begins, subjects are randomly assigned to a new market. In other words, we have fixed matching within supergames and random matching across supergames. Each supergame lasts at least 20 periods. From the 20th period onward, a random rule with a continuation probability of 7/10 determines whether play continues. The number of periods in all three rounds was determined ex ante and is the same in all sessions (24, 20 and 21 periods). Subjects knew they would play three supergames from the instructions and they also knew the termination probability.

3 Model

3.1 Setup

Consider a three-player game where players' action sets are the prices $\{p_{high}, p_{low}\}$. With p_i denoting player i's price, her payoff is generally denoted by $\pi_i(p_i, p_j, p_k)$, $i, j, k \in \{1, 2, 3\}$, where p_j and p_k are the prices of the rivals of player i, $i \neq j$, $i \neq k$, $j \neq k$, and where the identity of the rival players does not matter, that is, $\pi_i(p_i, p_j, p_k) = \pi_i(p_i, p_k, p_j)$. We use the notation $\pi^c, \pi^s, \pi^d, \pi^f$ and π^n as above in Table 1.

[14]See Honhon and Hyndman (2020) for an analysis of how matching schemes and reputation mechanisms affect cooperation in the repeated prisoner's dilemma.

3.2 Repeated-game Incentive Constraint

We analyze an infinitely repeated version of this game. Let time be indexed by $t = 0, ..., \infty$. Future periods are discounted by the factor δ.

Suppose the three players attempt to establish collusion on the p_{high} following a 'grim-trigger' strategy (GT): a player chooses p_{high} in $t = 0$ and keeps charging p_{high} as long as no one deviated in any previous period, otherwise she charges p_{low} from $t + 1, ..., \infty$. Playing GT is a subgame-perfect Nash equilibrium (SGPNE) if

$$\begin{aligned} \frac{\pi^c}{1-\delta} &\geq \pi^d + \frac{\delta \pi^n}{1-\delta} \\ \delta &\geq \frac{\pi^d - \pi^c}{\pi^d - \pi^n} = \frac{2}{3} \equiv \underline{\delta}_{GT} \end{aligned} \tag{1}$$

where the subscript GT indicates that all three participants are GT players.

Suppose now there are two players attempting to establish collusion via GT and the third player is an algorithm, committed to playing $pTFT$. We analyze the incentives of a GT player to deviate. If a GT player chooses p_{high}, she receives π^c in $t = 0, ..., \infty$ in equilibrium. The profit from a one-off deviation is π^d, as before. The punishment payoff in $t = 1$ does change: If player i deviates in $t = 0$, the price vector reads $(p_{low}, p_{high}, p_{high})$ and prompts the $pTFT$ algorithm to cooperate with 50% in $t = 1$. Either way, all players choose p_{low} from $t = 2$ on. Thus, the incentive constraint becomes

$$\frac{\pi^c}{1-\delta} \geq \pi^d + \delta \left(\frac{\pi^f + \pi^n}{2} \right) + \frac{\delta^2 \pi^n}{1-\delta}.$$

Solving for δ for the values employed in the experiment yields (a closed-form solution can be obtained, but is not informative)

$$\delta \gtrsim 0.69 \equiv \underline{\delta}_{pTFT}. \tag{2}$$

Here, the subscript $pTFT$ indicates that one of the three players is the $pTFT$ algorithm. Ensuring that (2) is met does not suffice for GT to be subgame-perfect. In the Appendix, we formally prove that GT is subgame-perfect despite the presence of the $pTFT$ player. We summarize by comparing (1) and (2):

Proposition 1. *The minimum discount factor required for collusion to be a SGPNE is lower for three GT players compared to two GT players and one pTFT algorithm:* $\underline{\delta}_{GT} < \underline{\delta}_{pTFT}$.

The intuition behind Proposition 1 is straightforward. GT and $pTFT$ are both cooperative strategies, but $pTFT$ is more forgiving. This raises the payoffs of a GT player after a defection and, accordingly, increases the minimum discount factor.[15]

3.3 Strategic Risk

The inequalities (1) and (2) are necessary conditions for GT to be subgame-perfect, but they do not reflect the coordination problems players face in the presence of multiple equilibria. Taking strategic risk into account is especially important when analyzing algorithms. The algorithm is committed to a strategy, whereas humans are not. So, the algorithm reduces strategic uncertainty. Merely to focus on incentives in a given collusion equilibrium and to ignore strategic risk would imply that we may miss the collusive impact algorithms may have.

To deal with strategic uncertainty, a growing literature on repeated prisoner's dilemmas (Blonski et al., 2011; Blonski and Spagnolo, 2015; Dal Bó and Fréchette, 2011, 2018; Green et al., 2015) borrows from Harsanyi and Selten's (1988) concept of risk dominance which can easily be applied to symmetric coordination games with two strategies. A strategy is risk-dominant if it is a best response to the other players mixing with equal probability between the two strategies. We follow Blonski et al. (2011), Blonski and Spagnolo (2015), Dal Bó and Fréchette (2011, 2018), and Green et al. (2015) in focusing on a simplified version of the game, the choice between two repeated-game strategies. We henceforth analyze the decision between the collusive GT and the non-cooperative 'always defect' strategy (AD). That is, players' action sets are now the repeated-game strategies

[15] Nevertheless, results from experiments with self-learning algorithms suggest that these algorithms learn to cooperate even after deviations and therefore pursue a more forgiving strategy than GT; see Calvano et al. (2020, section IV. C).

GT and AD.[16] Provided (1) and (2), respectively, hold, all players playing GT and all players playing AD are equilibria of this two-action game. Increasing δ reduces the riskiness of GT, and we solve for a new critical discount factor, δ^*, such that playing GT is the best response given that the other players randomize with equal probability between the two strategies GT and AD.

Consider three players choosing between GT and AD. When playing GT, there are two contingencies for the profit of player i in period $t = 0$: Provided the other two players also play GT (which happens with a probability of $1/4$), i obtains π^c. If at least one other player defects (probability $3/4$), i obtains $\pi^s = 0$ in period $t = 0$. If all players including i play GT in $t = 0$, i also obtains π^c in all future periods $t = 1, ..., \infty$. If at least one player defects in $t = 0$, i gets π^n in periods $t = 1, ..., \infty$. Thus, player i's expected payoff from playing GT is

$$\frac{1}{4}\left(\frac{\pi^c}{1-\delta}\right) + \frac{3}{4}\left(\pi^s + \frac{\delta\pi^n}{1-\delta}\right)$$

If player i instead plays AD, there are three possibilities. If both other players cooperate in $t = 0$ (which happens with a probability of $1/4$), i obtains π^d. If one rival player cooperates and the other defects (which happens with a probability of $1/2$), i obtains π^f. When both rival players defect (probability of $1/4$), i obtains π^n. In all three cases, i obtains π^n in $t = 1, ..., \infty$. Player i's expected payoff is

$$\frac{\pi^d}{4} + \frac{\pi^f}{2} + \frac{\pi^n}{4} + \frac{\delta\pi^n}{1-\delta}$$

Taking the difference in expected profits of GT and AD and solving for δ, we find that GT has a higher expected payoff than AD, if and only if

$$\delta \geq \frac{\pi^d + 2\pi^f - 3\pi^s + \pi^n - \pi^c}{\pi^d + 2\pi^f - 3\pi^s} = \frac{8}{9} \approx 0.89 \equiv \delta^*_{GT} \tag{3}$$

where $\delta^* \in (0, 1)$ denotes the critical discount factor in the presence of

[16] For the simplified version of the game with only two repeated-game strategies (GT and AD), Blonski and Spagnolo (2015) show that any collusive equilibrium is risk-dominant if GT is risk-dominant.

strategic risk and the subscript GT indicates that all three players are (potential) GT players. Note that $\delta^*_{GT} > \underline{\delta}_{GT}$ strictly and that payoffs π^s and π^f occur here – which is not the case for $\underline{\delta}$.

Now one of the three market participants is an algorithm committed to playing $pTFT$.We analyze the choice of the other two players between GT and AD. Suppose player i plays GT. Then there are only two contingencies: the other player plays either GT or she plays AD. Expected profits are accordingly

$$\frac{1}{2}\left(\frac{\pi^c}{1-\delta}\right) + \frac{1}{2}\left(\pi^s + \frac{\delta}{2}(\pi^f + \pi^n) + \delta^2 \frac{\pi^n}{1-\delta}\right)$$

If player i plays AD, she gets

$$\frac{1}{2}\left(\pi^d + \frac{\delta}{2}\left(\pi^f + \pi^n\right) + \frac{\delta^2 \pi^n}{1-\delta}\right) + \frac{1}{2}\left(\pi^f + \frac{\delta \pi^n}{1-\delta}\right)$$

We find that GT has a higher expected payoff if

$$\delta \geq \frac{\pi^d + \pi^f - \pi^c - \pi^s}{\pi^d + \pi^f - \pi^n - \pi^s} = \frac{17}{21} \approx 0.81 \equiv \delta^*_{pTFT} \tag{4}$$

Comparing (3) and (4), we obtain:

Proposition 2. *The minimum discount factor required in the presence of strategic uncertainty is higher for three GT players compared to two GT players and one $pTFT$ algorithm: $\delta^*_{GT} > \delta^*_{pTFT}$.*[17]

Whereas Propositions 1 and 2 imply contradicting effects, the existing experimental evidence suggests that δ^* has more explanatory power than $\underline{\delta}$ (Dal Bó and Fréchette, 2018). Blonski et al. (2011) highlight treatment comparisons where $\underline{\delta}$ and δ^* change in opposite directions, as in our experiment, and find that "the frequency of cooperation changes as predicted by changes in δ^*, contradicting predictions based on $\underline{\delta}$" (Blonski et al., 2011, p. 185).[18]

[17]The reader can verify that $\delta^*_{GT} > \delta^*_{pTFT}$ not only for our experimental parameters, but in general: Note that both the numerator and the denominator of δ^*_{GT} exceed their δ^*_{pTFT} counterparts by $\pi^f + \pi^n - 2\pi^s > 0$, hence are increasing δ^*_{GT}.

[18]Their analysis is often based on what they label as "class 2" data. In that class, the

4 Hypotheses

An algorithm may affect human behavior via several channels. We mainly focus on the *action channel* and the *belief channel*. These two channels may affect behavior differently. We further consider *other-regarding preferences* as a third channel.

We begin with actions. At least in the long run, human subjects will probably be influenced by the algorithm's actual price-setting behavior and its responses, including the punishments it triggers, and so on. In other words, the algorithm's actions will matter. Our $pTFT$ algorithm is more collusive than the average human and this should have a positive effect on the proportion of p_{high} choices. Based on Proposition 2 of our model, we expect that the Algorithm_ treatments will be more collusive than their Human_ counterparts. Whether this materializes also depends on expectations about the algorithm. The _Uncertain treatments, however, are identical in terms of the instructions and the possibility of an algorithm being present, so the beliefs cannot matter, but the actual play can. We hypothesize:

Hypothesis 1. *Cooperation rates in Algorithm_Uncertain are higher than those in Human_Uncertain.*

We turn to beliefs. Human subjects may expect the algorithm to play differently than humans. Responding to this belief, humans adjust their behavior accordingly.[19] But in which direction will the belief be affected? Farjam and Kirchkamp (2018) find that algorithms are perceived as "more rational", but in terms of expectations about cooperativeness this could go either way. Some findings indicate that humans may expect the algorithm to play less collusively than humans. Trust is an important part of successful collusion, and the literature on algorithm aversion suggests that humans trust algorithms less than other humans. News about algorithms beating

actual discount factor is above $\underline{\delta}$, but below δ^*, as is the case in our experiment.

[19] There is ample evidence that human subjects respond to beliefs about the action of others. In the prisoner's dilemma, there are two motives for defection (Ahn et al., 2001; Blanco et al., 2014; Charness et al., 2016). Subjects fear being exploited by others, but some may greedily also want to exploit others themselves.

humans at Chess or Go may corroborate this. Having said that, market interactions are not zero-sum games. As noted in the introduction, the collusive potential of algorithms is at the center of a widespread debate, and some of that debate has transpired to the popular press (see footnote 2). Altogether, it does not seem warranted to maintain a directed hypothesis here.

We accordingly formulate an Exploratory Research Question: Do subjects expect more or less cooperation from an algorithm than from a human opponent, and how will this impact the price level? In the two Algorithm_ treatments, the algorithm's actions are the same, but in Algorithm_Certain, subjects know for sure they face an algorithm, whereas in Algorithm_Uncertain, they might still be competing with a human. For the Human_ treatments, the third player is controlled by a human either way, but in Human_Uncertain, participants expect to meet an algorithm with 50% likelihood. We thus state:

Exploratory Research Question 2. *Do cooperation rates differ within the Algorithm_ or Human_Treatments?*

A third possible channel occurs when participants have other-regarding motives. In that case, subjects may play differently against an algorithm than against a human as a matter of principle. Upfront we note that purely outcome-based distributional preferences may not have impact. Our Algorithm_ treatments involve three human participants. The payout earned by the algorithm was paid out to a (passive) human participant. Therefore, other-regarding preferences based on monetary outcomes only cannot play a role.[20] By contrast, reciprocal behavior may actually have impact. The literature on intentions-based social preferences shows that choices from the same set of distributional alternatives depend on how the set was generated (Charness and Rabin, 2002). Subjects often reciprocate when they know they are playing against a human, but reciprocity may be less powerful when subjects know they are facing an algorithm (Mahmoodi et al., 2018; Zonca et al., 2021). A model by Iriş and Santos-Pinto (2013) shows

[20]In this context, we note that participants with non-selfish other-regarding preferences do not necessarily cooperate more. See Hernández-Lagos et al. (2017).

that collusion is easier to maintain when subjects are reciprocal. If reciprocal behavior in this sense has force, then the implications are the same as above when subjects have skeptical beliefs (that is, when subjects expect the algorithm to be less cooperative). Whereas we leave the Exploratory Research Question 2 unaltered, we note that the interpretation of any differences in the data may be due to either motive (skeptical beliefs or lack of reciprocity towards the algorithm).

Concluding, we hypothesize about the two _Certain treatments. The actual play of the algorithm, on the one hand, and beliefs, on the other, imply an ambiguous effect of algorithms. We nevertheless hypothesize that the use of algorithms will have a positive overall impact on collusion because we provide ample opportunity for learning (three relatively long repeated games). Given these learning opportunities, even algorithm-averse subjects may update their beliefs and adjust them according to the more cooperative behavior of the algorithm. We hypothesize:

Hypothesis 3. *Cooperation rates in Algorithm_Certain are higher than those in Human_Certain.*

5 Procedures

Subjects were recruited from pools of subjects who had previously volunteered to participate in lab experiments. The experiments involved 309 participants in total. None of the subjects participated in more than one session. We had 16 sessions in total, four for each of the four treatments, see Table 3. The session size varied between 12 and 30 participants. The experimental sessions were conducted at labs in Düsseldorf and MPI Bonn between August 2019 and October 2020. No sessions were conducted between early March and mid-July 2020, due to the pandemic. Sessions from mid-July 2020 on were conducted under (by then) common hygiene rules. See Table A.1 in the Additional Material for session details.

Upon arrival at the laboratory, subjects were randomly assigned to a cubicle, using tokens with the cubicle numbers. After a sufficient number of participants had arrived, the experiment started and participants

Treatment	# sessions	# subjects	# markets
Human_Certain	4	72	24
Human_Uncertain	4	75	25
Algorithm_Uncertain	4	86	28
Algorithm_Certain	4	78	26

Table 3: Number of sessions, participants and markets per treatment.

received a hard copy of the instructions in German. While reading the instructions, subjects were allowed to ask questions privately in their cubicles. Afterwards, control questions made sure everyone had understood the task.

The decision-making parts were conducted as follows. We programmed the experiment in z-Tree (Fischbacher, 2007). In each period, the subjects had to decide by clicking a button whether they wanted to set p_{high} or p_{low}. After everyone had decided, an information screen displayed the choices of all three firms in the market, always in the same order[21], and informed subjects about their payoff. At the end of a supergame, the individual overall payoff for that supergame was displayed and the subjects were informed that they would now be assigned to a new market, unless it was the last supergame.

We used an Experimental Currency Unit, where 1,000 ECU corresponded to 1 Euro. One of the three supergames was randomly chosen for payout. At the end of the third supergame, the subjects were informed about the supergame selected for payout and their total earnings.

In the _Uncertain treatments, we further asked participants whether they thought an algorithm was present in the experiment. This was done at the end, after the last period of the last supergame. Subjects had to enter a number between zero and 100, expressing how confident they were that an algorithm was in the market. They were paid up to 2 euros for a correct guess: Given a guess $x \in \{0, 1, 2, ..., 100\}$ that an algorithm was present, the payoff was $2x/100$ if this was actually the case and $2 - 2x/100$ if not. Participants for whom the algorithm decided were paid 1 euro flat instead.

[21] This implies that subjects were able to track the individual actions of each opponent. This might facilitate understanding rivals' strategies and possibly also to detecting the algorithm.

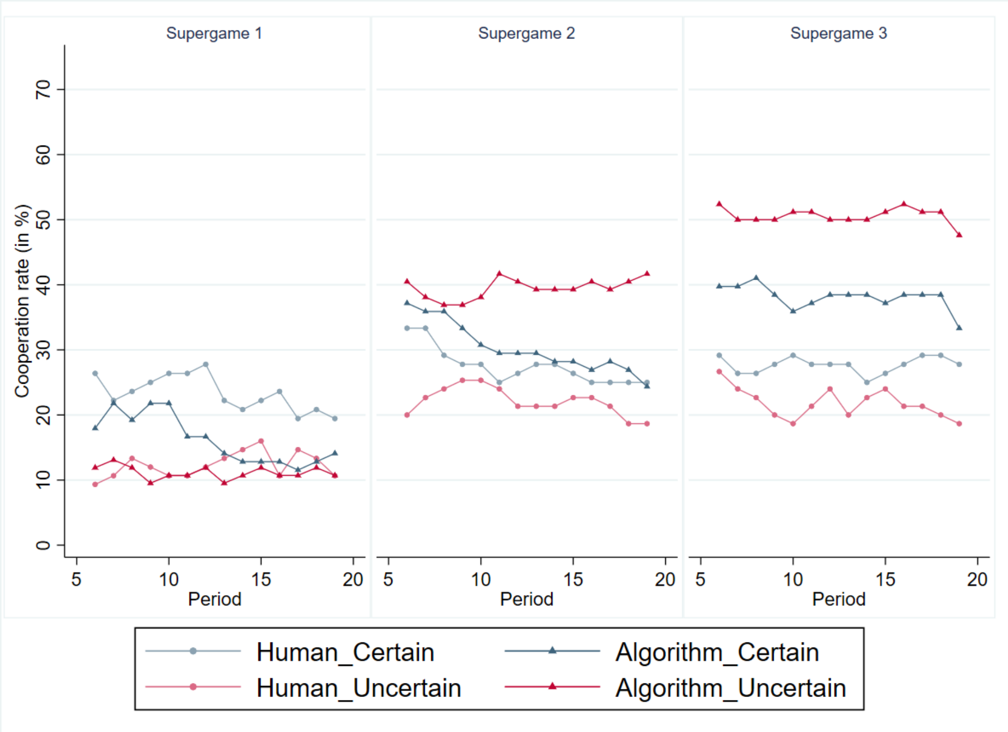

Figure 1: Cooperation rates over time (periods 6 to 19).

The sessions lasted for about 60 minutes. The average payment was 17.73 euro, including a show-up fee.

6 Results

6.1 Overview

Figure 1 shows how cooperation rates[22] in the different treatments develop over time and supergames.[23] Generally, cooperation increases across supergames: In supergame 1, cooperation rates vary roughly between zero and less than 30%, whereas in supergame 3 they vary between 20 and more than 50%. It appears participants learn to collude tacitly with repetitions of the supergame, confirming the results of Bigoni et al. (2015), Dal Bó and Fréchette (2011, 2018), and Fudenberg et al. (2012). A closer look

[22]The cooperation rate is defined as the number of p_{high} choices divided by the total number of choices, given a treatment or period of play.

[23]To exclude restart and endgame effects, we focus on periods 6 to 19. The same graph including all periods can be found in Figure A.1 in the Additional Material.

	SG 1	*SG 2*	*SG 3*	*All*
Human_Uncertain	0.123	0.221	0.218	0.187
	(0.328)	(0.415)	(0.413)	(0.390)
Algorithm_Uncertain	0.111	0.395	0.506	0.337
	(0.315)	(0.489)	(0.500)	(0.473)
Human_Certain	0.233	0.275	0.277	0.262
	(0.423)	(0.447)	(0.448)	(0.440)
Algorithm_Certain	0.162	0.303	0.381	0.282
	(0.369)	(0.460)	(0.486)	(0.450)

Standard deviations in parentheses.

Table 4: Average cooperation rates (periods 6 to 19) in supergames (SG) 1 to 3 and across all supergames.

reveals that cooperation rates improve for all treatments in supergame 2, but when comparing supergames 2 and 3, only the treatments involving an algorithm increase substantially.[24]

Complementing Figure 1, Table 4 shows the cooperation rates averaged across periods 6 to 19. We note that the Algorithm_ treatments have higher averages than their Human_ counterparts in supergames 2 and 3. Taking all supergames into account, the highest cooperation rate is observed in Algorithm_Uncertain (0.337), followed by Algorithm_Certain (0.282) which, in turn, exhibits more cooperation than Human_Certain (0.262). We find higher cooperation in Human_Certain than in Human_Uncertain (0.187). This order does not change if we include all periods or focus only on the decisions of human subjects (that is, if we exclude the algorithms' decisions). See Table A.2 and Table A.3 in the Additional Material for details.

How successful are the firms in actually establishing the collusive outcome? Figure 2 shows the percentages of three outcomes for the four treatments: "tacit collusion" indicates successful cooperation – all firms choose p_{high}; "competition" means that all firms charge p_{low}; and "failed collusion" occurs when at least one firm chooses p_{low} and at least one firm tried

[24]There is a very minor increase of cooperation in Human_Certain by 0.2 percentage points when comparing supergames 2 and 3. See Table 4.

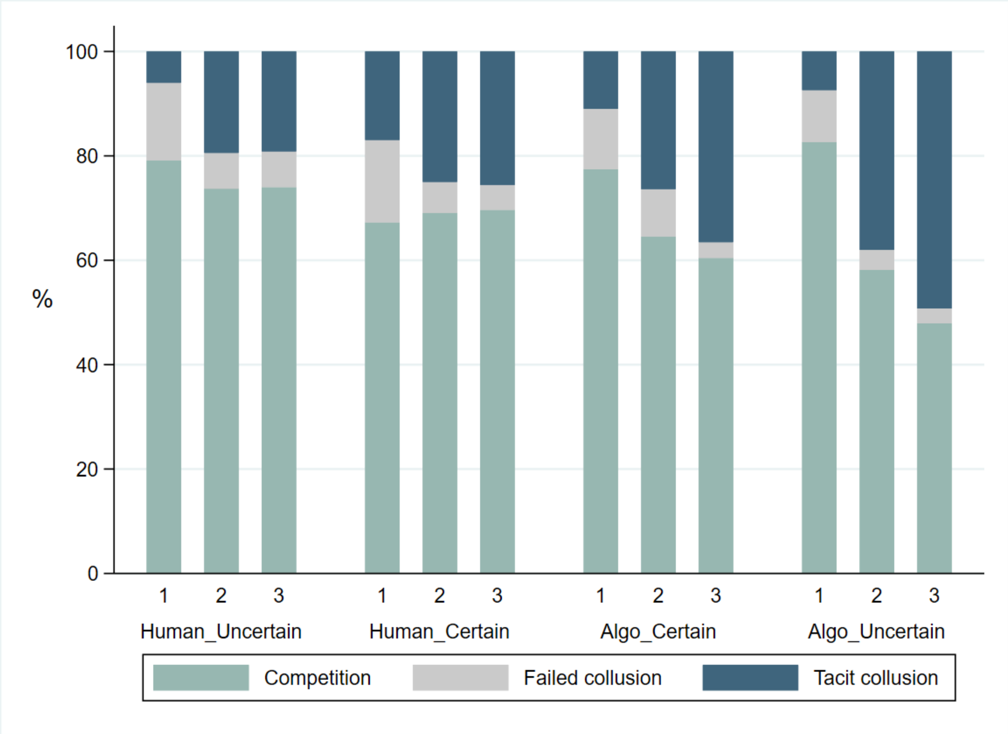

Figure 2: Collusive and competitive outcomes (periods 6 to 19).

to collude – this is miscoordination. Again, it becomes clear that, from the second supergame on, successful coordination on the high price occurs more often in Algorithm_Uncertain and Algorithm_Certain. In supergame 3, the two extremes are conspicuous: Algorithm_Uncertain with roughly 50% competition, whereas Human_Certain involved almost 80% competition. The share of outcomes with miscoordination (failed collusion) is remarkably small in all treatments, meaning that subjects quickly coordinate on either the cooperative or the competitive outcome. This is also apparent from the quick drop in cooperation in the first five periods (see Figure A.1 in the Additional Material).

6.2 Treatment Differences

We now systematically test our hypotheses and make statistically reliable statements about treatment effects. Throughout, we take the possible dependence of observations (individual cooperation decisions) into account using bootstrapping standard errors at the session level.[25] See Cameron et al. (2008).

Table 5 shows the results of a linear probability model and highlights the main treatment effects we observe. Our dependent variable is whether or not a firm (participant or algorithm) cooperates in a given period. We run two sets of regressions. First, we include as explanatory variables only Algorithm (reflecting Algorithm_Uncertain and Algorithm_Certain) and Certain (reflecting Algorithm_Certain and Human_Certain). Second, we use the three treatments Algorithm_Uncertain and Human_Certain and Algorithm_Certain as explanatory variables. In all regressions, Human_Uncertain serves as the baseline treatment, reflected in the constant. We further include dummies for the initial and terminal periods of play. We report the results separately for the three supergames and jointly for all supergames where we add a cardinal variable for supergame (equal to zero for supergame 1, such that the constant reflects supergame 1).

[25]As an alternative specification, we collapsed the data at the session/period level, such that we obtained one average cooperation rate per session and period, and we handled the data as a panel with random effects at the session level. The results are virtually the same in terms of statistical significance. Put differently, our results are also robust with this more conservative approach.

	Supergame 1		*Supergame 2*		*Supergame 3*		*All*	
Algorithm	-0.0225		0.108**		0.185**		0.0847	
	(0.0528)		(0.0526)		(0.0813)		(0.0516)	
Certain	0.0706		0.000116		-0.0292		0.0166	
	(0.0542)		(0.0515)		(0.0833)		(0.0523)	
Human_Certain		0.100		0.0691		0.0466		0.0733
		(0.0966)		(0.0839)		(0.112)		(0.0818)
Algo_Uncertain		0.00490		0.172***		0.255**		0.137**
		(0.0566)		(0.0654)		(0.110)		(0.0556)
Algo_Certain		0.0486		0.109*		0.157*		0.102**
		(0.0569)		(0.0635)		(0.0898)		(0.0468)
Periods 1-5	0.0867***	0.0867***	0.129***	0.129***	0.116***	0.116***	0.110***	0.110***
	(0.0234)	(0.0235)	(0.0177)	(0.0173)	(0.0199)	(0.0198)	(0.0133)	(0.0132)
Periods 20-25	-0.0524***	-0.0524***	-0.0522***	-0.0522***	-0.129***	-0.129***	-0.0821***	-0.0821***
	(0.0159)	(0.0159)	(0.0160)	(0.0159)	(0.0292)	(0.0289)	(0.0108)	(0.0107)
Supergame							0.0968***	0.0968***
							(0.0216)	(0.0210)
Constant	0.133***	0.118***	0.245***	0.211***	0.268***	0.231***	0.120***	0.0923***
	(0.0405)	(0.0372)	(0.0518)	(0.0561)	(0.0625)	(0.0531)	(0.0401)	(0.0309)
Obs.	7,416	7,416	6,180	6,180	6,489	6,489	20,085	20,085
R^2	0.025	0.027	0.029	0.033	0.057	0.063	0.062	0.066

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Treatment effects, all periods, linear probability model.

The impact of Algorithm_ in the regressions reported in Table 5 is positive and statistically significant from supergame 2 onward. So, when analyzing them jointly, the two Algorithm_ treatments cooperate better than the two Human_ treatments. When we compare the individual treatments directly, we find that Algorithm_Uncertain and Human_Uncertain differ significantly, consistent with Hypothesis 1 (*SG* 2, 3 and all). Regarding Hypothesis 3, we observe that Algorithm_Certain and Human_Certain do not differ significantly (post-hoc test, $p > 0.366$, any *SG*)

Result 1. *The Algorithm_ treatments jointly exhibit significantly higher cooperation rates than the Human_ treatments. Cooperation rates are significantly higher in Algorithm_Uncertain compared to Human_Uncertain. We find no statistically significant effects when comparing Algorithm_Certain and Human_Certain.*

Moving on to the comparison of _Certain and _Uncertain treatments (Exploratory Research Question 2), we find that the general impact of _Certain is positive, small, and insignificant. Likewise, Human_Uncertain does not differ from the baseline Human_Certain. Running post-hoc tests, we further find no significant differences between Algorithm_Uncertain and Algorithm_Certain ($p > 0.153$ in any *SG*). Evidence for the way beliefs affect behavior can nevertheless be detected. The mean cooperation rates correspond to the notion than human participants maintain skeptical expectations about the algorithms decisions. For the Algorithm_ treatments, we find (insignificantly) more cooperation in _Uncertain than in _Certain in supergames two and three and all supergames. For the Human_ variants, subjects were more cooperative in _Certain than in _Uncertain in all supergames. Thus, human subjects become less cooperative when they suspect that one of the opponents is an algorithm compared to when this is not the case, and when they know for sure that one of the opponents is controlled by an algorithm as compared to the case in which they only have this suspect. As outlined above, a lack of reciprocity towards the algorithm is likewise an appropriate interpretation of this result.

Result 2. *We find no statistically significant effects between the _Uncertain and the _Certain treatments.*

Another piece with suggestive evidence on expectations comes from the incentivized guess in the _Uncertain treatments. This is what we analyze in detail next.

6.3 Beliefs about the Presence of an Algorithm

	Guess	
Algorithm	-12.19**	-8.663**
	(4.916)	(4.374)
Sum of miscoordinated outcomes		1.303***
		(0.361)
Constant	58.06***	43.78***
	(3.920)	(5.216)
Obs.	131	131
R^2	0.027	0.072

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Incentivized guess about the presence of an algorithm in the _Uncertain treatments, linear probability model.

In the two _Uncertain treatments, we asked participants (incentivized) at the end of the experiment about their beliefs of whether one of the firms was equipped with an algorithm. Subjects had to state a probability (a number between zero and 100) that an "algorithm was present in the experiment."

It turns out that subjects in Human_Uncertain maintain an average belief of 58.05%, whereas those in Algorithm_Uncertain have a belief of 45.87%. That is, participants are *more* inclined to believe an algorithm was present when this was *not* the case. Table 6 (first column) shows the results of a linear probability regression with data from Algorithm_Uncertain and Human_Uncertain and *algorithm* as an explanatory variable. The variable *algorithm* is negative and significant ($p < 0.05$).

Result 3. *Guesses about an algorithm being present in the market are significantly lower in Algorithm_Uncertain compared to Human_Uncertain.*

One possible explanation for this surprising finding is that participants associate cooperation with human behavior and not an algorithm.[26] Cooperation rates in Algorithm_Uncertain are significantly higher than in Human_Uncertain, and the lower performance of Human_Uncertain is clearly associated with a higher belief of an algorithm being present. When we add as an explanatory variable to the regressions in Table 6 (second column) the number of miscoordinated outcomes (one or two firms chooses p_{low} and at least one firm chooses p_{high}) which a participant experiences during the entire course of the experiment, this variable is positive and highly significant ($p < 0.01$), and the magnitude of the *algorithm* coefficient decreases, but is still significant ($p < 0.05$). We take this as evidence that the participants expect the algorithm to be more competitive than humans.[27]

6.4 Differences Between Human and Algorithmic Play

A first difference between human and algorithmic play is that the $pTFT$ strategy begins a supergame by choosing the high price with probability one, in contrast to the average human subject. The data indicate that the algorithm has a substantial effect on the cooperation rate in the first period throughout. This effect is noteworthy because of the significance of period-one behavior for overall cooperation. However, we refrain from stating this result formally because it is immediate from the way the algorithm is programmed.

Figure 3 is an alluvial flow diagram that illustrates how humans compare to the algorithm with respect to individual decisions. It is based on decisions by humans only, using data from all treatments, periods 1 to 19,

[26]According to Lee (2018), participants rate algorithmic decisions as less fair, trust algorithmic decisions less, and feel less positive about algorithmic decisions when it comes to tasks requiring human skills. With mechanical tasks, the fairness and trustworthiness of algorithms were attributed to their perceived efficiency and objectivity.

[27]Quotes from a post-experimental questionnaire are consistent with this conclusion. We emphasize that these subjects did not play a Human_ variant, so the comparisons they draw reflect their beliefs: "*Nice experiment, the inclusion of the algorithm was a clever idea and could damage the mutual trust between the companies so much that they basically sold low even though this was against their own interests*", or "*The introduction of the algorithm makes it much harder to communicate about prices, as ideally each company sets a high price so that the market as a whole makes the most profit. However, since the algorithm is (or at least seems to be) unpredictable in such a short period of time, this is much more difficult to communicate.*"

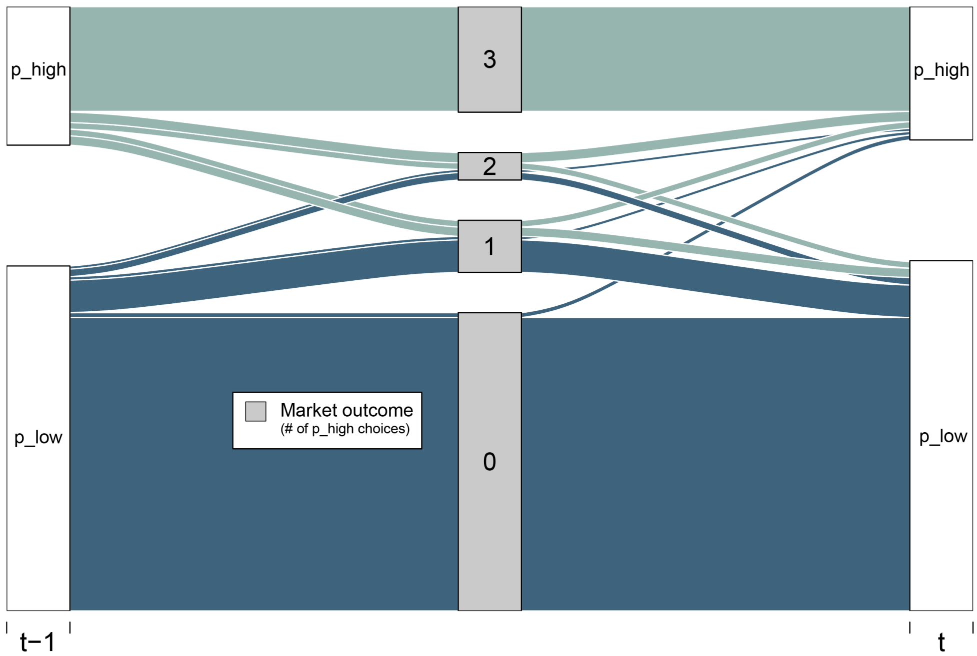

Figure 3: Alluvial flow diagram of choices by human subjects (all supergames, periods 1 to 19).

and all supergames.[28] The figure shows how participants' decisions in period $t-1$ (left-hand side of the figure) map into market outcomes (middle), and how conditional on these outcomes decisions in period t emerge. The market outcome is defined as the number of p_{high} choices of all players in a market, including the subject herself and possibly the algorithm.

Let us be more specific. Humans choose p_{high} at a rate of roughly 30% (light segment on the left) and, accordingly, p_{low} at 70% (dark segment). Due to the high degree of coordination in markets, outcomes labeled 0 ("all p_{low}") and 3 ("all p_{high}") result most frequently. If the coordination in markets fails, outcomes 1 ("one p_{high}, two p_{low}") and 2 ("two p_{high}, one p_{low}") result. The stream from the gray outcome boxes then indicates how humans decided conditional on outcome. Their own $t-1$ decision can be identified by the color (light blue for p_{high} and dark blue for p_{low}).

The algorithm always chooses p_{high} if both competitors previously chose

[28]See Table A.4 in the Additional Material, where we provide the same analysis for the individual treatments. Differences between treatments are minor. We dropped the data from period 20 on because we are not specifically interested in the end-game behavior humans exhibit.

p_{high}—how do humans behave here? Overall, it turns out human participants are also highly likely to play p_{high} (92.7%). But there are substantial differences when the own prior choice is taken into account. Provided that they themselves previously played p_{high}, human subjects almost always play p_{high} again (99.1%).[29] When we look at the human subjects who played p_{low} while both their competitors chose p_{high} ("two p_{high}, one p_{low}"), we see that roughly 29.3% cooperate, whereas the algorithm would play 100% p_{high} here, too.

Whereas Figure 3 is based on data from all treatments, there are some minor treatment differences regarding the observations where both competitors previously chose p_{high}. As Table A.4 indicates, cooperation rates go down when one opponent could be an algorithm, consistent with the hypothesis that humans maintain skeptical beliefs regarding the algorithm, or that they do not exhibit reciprocal behavior towards the computer.[30] Specifically, human subjects become (insignificantly) less cooperative when they suspect that one of the opponents is an algorithm (Human_Certain vs. Human_Uncertain), and when they know for sure that one of the opponents is controlled by an algorithm (Algorithm_Certain vs. Algorithm_Uncertain and Human_Certain vs. Algorithm_Certain). It appears that the stronger the belief is that one of the opponents is an algorithm, the less cooperative play becomes.

Differences between humans and the algorithm also become apparent in markets with mixed outcomes where one competitor chose p_{high} and the other one p_{low} in $t-1$. The probability that the algorithm will play cooperatively is 50%, whereas that of the human subjects is only 26.2%. Again, Figure 3 shows the differences between subjects who played p_{high} previously and those who chose p_{low}.[31] The cooperatively playing subjects stuck to their strategy with a probability of 61.2%, which is significantly

[29] In 26 out of 3,007 observations, these subjects chose p_{low}, which is too little to be visible in Figure 3.

[30] A referee suggested the notion that the potential presence of an algorithm offers humans a moral wiggle room to justify deviations, which is similar in spirit to the lack of reciprocity.

[31] For two-player prisoner's dilemma experiments, Breitmoser (2015) suggests that subjects play a "semi-grim" strategy, such that subjects randomize across choices regardless of their own previous choice.

different from the 50% rate of the algorithm ($p < 0.001$).[32] But such attempts to establish collusive conduct are hampered by the behavior of competitive rivals who rarely choose the high price (9.8%), which is likewise significantly different from the 50% rate of the algorithm ($p < 0.001$).

How about the potentially negative effect of the algorithm when both rival firms chose p_{low} previously? In this case, the algorithm would never choose p_{high}. But this does not differ much for human subjects who cooperate with 3.7 %. Conspicuously, the cooperative playing subjects continue their strategy with a relatively high probability (41.9%), while the competitive rivals play *p_high* only in very few cases (1.7%).

Overall, the probability of successful collusion, irrespectively of the previous market outcome, is higher in Algorithm_ (27.4%) than in Human_ treatments (18.3%). The algorithm is less cooperative than the human subjects when it comes to attempts to establish a collusive outcome, but much more cooperative than subjects who chose p_{low} before. It seems that the human subjects rarely modify their strategy, trying instead to avoid a change in their price decision.

6.5 Profits

If the algorithm treatments exhibit more cooperation, this suggests that all firms benefit in terms of higher profits. As we see more cooperation, the mean profits in Algorithm_ are actually higher than in Human_, so subjects earn more if an algorithm is present. In Table 7 in the Appendix, we analyze this systematically. The table provides the results of linear regressions where the dependent variable is the profit subjects earn from period 6 to 19. The explanatory variables include three treatment variables, such that Human_Uncertain is reflected by the constant. Algorithm_Uncertain is significant except in the first supergame. In a simpler regression where Algorithm and Certain replace the three treatment variables, the positive effect of Algorithm on profits is significant in the second ($p < 0.1$) and third supergame ($p < 0.05$).

By distinguishing between humans and algorithms, we can analyze who

[32] Linear regression on cooperation rate when one rival chose p_{high}, the other one p_{low}, and the own choice was p_{high} (p_{low}, respectively) in $t-1$, bootstrapped standard errors.

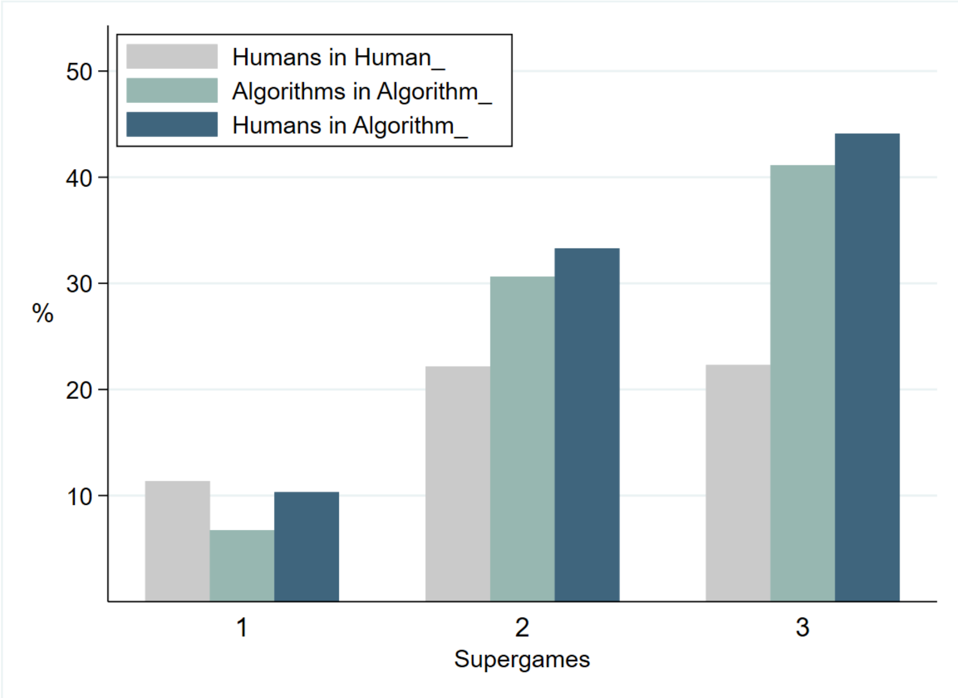

Figure 4: Profits in percent above Nash (periods 6 to 19).

benefits most from the presence of the algorithm. Figure 4 measures profits relative to static Nash earnings (0%) and to perfect collusion (100%).[33] We see that subjects equipped with an algorithm earn substantially less than their competitors in every supergame. We add to the regressions in 7 the dummy variable "role" which equals one when the player is an algorithm. Taking all supergames into account, the difference is statistically significant ($p < 0.01$). The negative effect of "role" is also significant in the first ($p < 0.1$) and the third supergame ($p < 0.001$). Although the algorithm helps to increase the group's profit, it performs significantly worse than their competitors. This suggests a coordination problem in that no firm wants to adopt the algorithm first.

Result 4. *Profits are significantly higher in the Algorithm_ treatments compared to the Human_ treatments. In the Algorithm_ treatments, participants represented by an algorithm earn significantly less than participants who decide themselves for their firm.*

[33] Formally, the index in Figure 4 is defined as (observed profit − Nash profit)/(collusive profit − Nash profit).

7 Conclusion

In this paper, we analyze the impact of algorithms on collusion in hybrid markets where humans interact with algorithms. The analysis of human-computer interaction is important because most markets in the field are heterogeneous and firms cannot be sure of whether their opponents are using algorithms for their pricing decision, nor do they know which type of algorithm competitors might use.[34] Recent literature (British Competition and Markets Authority, 2018; Musolff, 2021; Wieting and Sapi, 2021) investigates relatively simple algorithms and suggest that such straightforward pricing rules are (at least currently) empirically dominant in the field and may actually increase the risk of tacit collusion. This raises the question of impact algorithms have on hybrid markets where the algorithms interact with humans.

We study these issues in experimental markets with three firms where one firm is equipped with an algorithm. The algorithm, if present, plays proportional tit-for-tat (Axelrod, 1984; Hilbe et al., 2015), a simple and transparent strategy. We further vary whether the human participants know (in a non-deceptive way) about the presence of the algorithm. Participants of the experiments played three indefinitely repeated games.

We report three main sets of results. First, regarding the competitiveness of markets, we find that our algorithm significantly increases prices, consistent with a repeated-game model that accounts for strategic risk (Blonski et al., 2011; Blonski and Spagnolo, 2015; Dal Bó and Fréchette, 2011, 2018; Green et al., 2015). This finding confirms the anti-competitive potential algorithms have, even when interacting with humans. Moreover, it suggests that the collusive effects of algorithms are unlikely to be fully mitigated by the presence of humans. In other words, we cannot rely on humans to discipline the collusive behavior of algorithms.

Our second finding concerns participants' expectations when they interact with an algorithm. Largely, it appears that expectations (the (un)certainty that an algorithm is around) do not significantly affect pric-

[34] Explicitly communicating and agreeing on the use of algorithms has been penalized as a violation of cartel law. See Poster Cartel case: US Department of Justice, Apr. 6, 2015, Press Release no. 15-421, and British Competition and Markets Authority, Aug. 12, 2016, Case 50223.

ing. Intriguingly, when we elicit post-experiment beliefs about the nature of the co-players, participants are significantly more inclined to believe an algorithm was present when this was not the case. Specifically, humans appear to associate miscoordination with algorithmic play, whereas, in fact, the algorithm more frequently leads to successful cooperation. These results are broadly consistent with findings on algorithm aversion (Dietvorst and Bharti, 2020; Dietvorst et al., 2016, 2015). The results are also consistent with the notion that subjects behave reciprocally to other humans, but not to an algorithm (Charness and Rabin, 2002; Iriş and Santos-Pinto, 2013; Mahmoodi et al., 2018; Zonca et al., 2021).

A third set of findings concerns the profitability of employing an algorithm. We find that the firms for which the algorithm decided earn significantly less profit. This suggests that firms want their rivals to adopt the algorithm first: Firms face a coordination problem when it comes to delegating decisions to algorithms. Tacit collusion seems feasible, but requires algorithms with a certain degree of cooperative commitment. Therefore, a firm must be willing to accept setup costs. That said, this effect could be moderated by other benefits of algorithms, such as a higher frequency of pricing or better demand forecasting (Brown and MacKay, 2022; Miklós-Thal and Tucker, 2019). The coordination problem seems mitigated by the fact that algorithms are generally on the rise, but we note that a rising share of algorithmic players *per se* does not preclude the coordination problem.

Our results suggest promising topics for future research. One possible extension would be not to impose the use of the algorithm exogenously, but instead to let subjects choose whether they want to employ algorithms. Algorithm aversion may preclude this, but demonstrating the force of algorithms may cure this reluctance. In addition, the aforementioned coordination problem might be significant. One may further consider experiments where subjects decide which algorithm to employ.

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Appendix

Proof that GT is Subgame-perfect

In this Appendix, we prove that GT is also a subgame-perfect strategy when one of the three players is the $pTFT$ algorithm. Demonstrating that the incentive constraint (2) is met is generally *not* sufficient for GT to be subgame-perfect.[35]

Consider strategy profiles (p_i, p_j, p_k). Players i and j are GT players, and player k is the $pTFT$ player. Histories may end in $2^3 = 8$ different profiles. In equilibrium, players play $(p_{high}, p_{high}, p_{high})$ throughout, and in the main text, we show that (2) ensures i and j prefer not to deviate. We next analyze out-of-equilibrium histories ending in the other seven profiles.

A straightforward case are histories ending in $(p_{low}, p_{low}, p_{low})$. All players defect in $t+1$, and deviating (to p_{high}) does not pay for player i, consistent with GT. Likewise, following $(p_{low}, p_{low}, p_{high})$, all players defect in $t+1$, ensuring GT is a best response in the subgames following this outcome.

The five remaining profiles have in common that at least one player chooses p_{low} and at least one player selects p_{high}. These five profiles are $(p_{high}, p_{low}, \quad \cdot \quad)$, $(p_{high}, p_{high}, p_{low})$, and $(p_{low}, p_{high}, \quad \cdot \quad)$. In all cases, the $pTFT$ algorithm cooperates in $t+1$ with at least 50% (in the $(p_{high}, p_{high}, p_{low})$ case with 100%), whereas the GT players should choose p_{low}. A possible one-off deviation for a GT player is p_{high} in the next period. But since the second GT player will defect in $t+1$, such a deviation would yield a zero payoff, whereas sticking to GT (by choosing p_{low} from $t+1$ on) would yield (at least) π^n. It follows that GT is also a best response in the subgames following these five profiles. Hence, GT is also subgame-perfect in the presence of the $pTFT$ player, provided (2) is met.

[35] As an aside, we note that tit-for-tat strategies themselves are often not subgame-perfect (for two-player examples, see Osborne (2004)). But since in our case the algorithm is programmed to play $pTFT$, it will not deviate.

Profits

	Supergame 1		*Supergame 2*		*Supergame 3*		*All*	
Human_Certain	35.09	35.09	17.83	17.83	20.65	20.65	24.52	24.52
	(38.51)	(38.51)	(27.51)	(27.51)	(42.24)	(42.24)	(28.59)	(28.59)
Algo_Uncertain	4.473	8.283	59.46***	62.32***	96.29**	99.47**	53.41***	56.69***
	(19.63)	(19.61)	(21.44)	(21.68)	(42.87)	(42.80)	(19.42)	(19.49)
Algo_Certain	15.96	19.77	22.22	25.08	55.67	58.84*	31.28*	34.57**
	(23.39)	(23.14)	(21.19)	(21.23)	(33.86)	(33.94)	(16.51)	(16.60)
Role		-11.43*		-8.571		-9.524***		-9.841***
		(6.521)		(5.633)		(1.045)		(3.542)
Supergame							36.84***	36.84***
							(7.623)	(7.623)
Constant	499.2***	499.2***	542.2***	542.2***	541.3***	541.3***	490.7***	490.7***
	(13.48)	(13.48)	(18.06)	(18.06)	(20.42)	(20.42)	(8.487)	(8.487)
Observations	4,326	4,326	4,326	4,326	4,326	4,326	12,978	12,978
R-squared	0.005	0.005	0.015	0.015	0.042	0.043	0.037	0.037

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Total profits, periods 6 to 19, OLS regression.

A Additional Material

Session details

Date	Session	# Part.	# Markets	Lab[a]	COVID-19
28 August, 2019	3.1	21	7	Düsseldorf	0
11 September, 2019	4.1	24	8	Düsseldorf	0
11 September, 2019	3.2	21	7	Düsseldorf	0
12 September, 2019	4.2	18	6	Düsseldorf	0
04 March, 2020	3.3	24	8	Bonn	0
05 March, 2020	1.1	21	7	Bonn	0
05 March, 2020	1.2	21	7	Bonn	0
05 March, 2020	2.1	30	10	Bonn	0
06 July, 2020	2.2	18	6	Düsseldorf	1
05 August, 2020	1.3	18	6	Düsseldorf	1
02 September, 2020	2.3	15	5	Düsseldorf	1
22 September, 2020	4.3	18	6	Bonn	1
13 October, 2020	4.4	18	6	Bonn	1
14 October, 2020	2.4	12	4	Bonn	1
14 October, 2020	3.4	18	6	Bonn	1
16 October, 2020	1.4	12	4	Düsseldorf	1

Table A.1: Session Details

[a] As a show-up fee, the participants received 5 euros in Bonn and 4 euros in Düsseldorf. During the COVID-19 pandemic, the fee was increased to 8 euros in Düsseldorf from mid-July 2020 on. This in line with Schulz et al. (2019), who find that moderately different show-up fees had no influence on the behavior of the participants.

Overview Using Data from All Periods

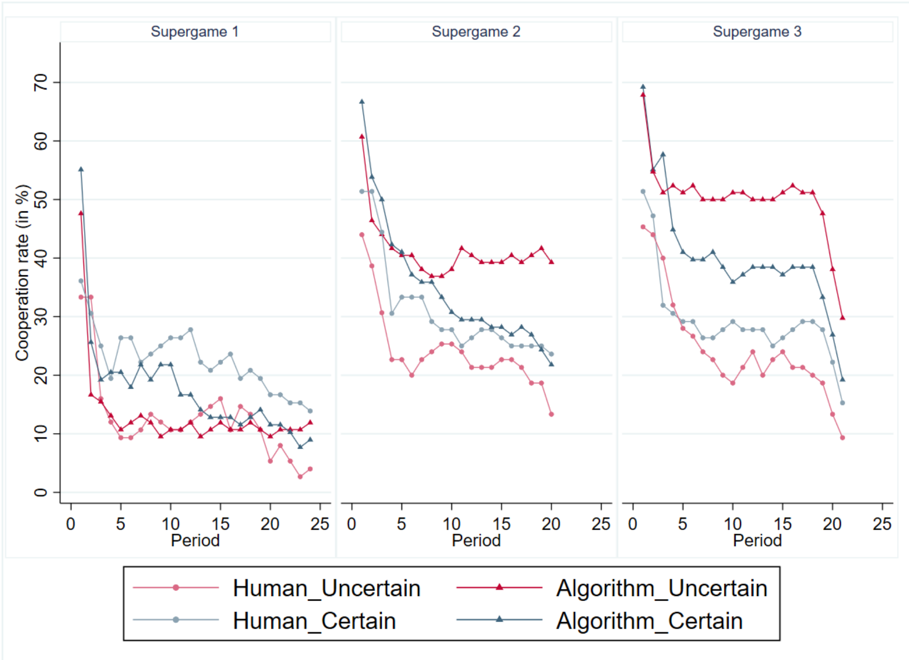

Figure A.1: Cooperation rates over time (all periods).

	Supergame 1	*Supergame 2*	*Supergame 3*	*All*
Human_U	0.126	0.241	0.246	0.200
	(0.331)	(0.428)	(0.431)	(0.400)
Algo_U	0.130	0.412	0.502	0.337
	(0.337)	(0.492)	(0.500)	(0.473)
Human_C	0.226	0.310	0.293	0.273
	(0.418)	(0.463)	(0.455)	(0.446)
Algo_C	0.174	0.350	0.404	0.302
	(0.379)	(0.477)	(0.491)	(0.459)

Standard deviations in parentheses.

Table A.2: Average cooperation rates (all periods).

Data of Human Subjects Only

	Supergame 1	*Supergame 2*	*Supergame 3*	*All*
Human_U	0.123	0.221	0.218	0.187
	(0.328)	(0.415)	(0.413)	(0.390)
Algorithm_U	0.112	0.395	0.504	0.337
	(0.316)	(0.489)	(0.500)	(0.473)
Human_C	0.233	0.275	0.277	0.262
	(0.423)	(0.447)	(0.448)	(0.440)
Algorithm_C	0.159	0.297	0.378	0.278
	(0.366)	(0.457)	(0.485)	(0.448)

Standard deviations in parentheses.

Table A.3: Average cooperation rates (human subjects, periods 6 to 19).

	Rival behavior in $t-1$			
	Two Low	*High/Low*	*Two High*	*Total*
Human_U	0.0286	0.212	0.962	0.187
	(0.167)	(0.409)	(0.192)	(0.390)
Algorithm_U	0.0251	0.178	0.987	0.337
	(0.157)	(0.384)	(0.115)	(0.473)
Human_C	0.0273	0.240	0.974	0.262
	(0.163)	(0.428)	(0.158)	(0.440)
Algorithm_C	0.0242	0.213	0.948	0.278
	(0.154)	(0.411)	(0.223)	(0.448)
Total	0.0267	0.216	0.969	0.260
	(0.161)	(0.412)	(0.172)	(0.438)

Standard deviations in parentheses.

Table A.4: Average cooperation rates with respect to the previous choices of rivals 1 and 2 (human subjects, period 6-19).

Treatments Effect with Probit Model

	Supergame 1		*Supergame 2*		*Supergame 3*		*All*	
Algorithm	-0.0907	0.0284	0.304*	0.490**	0.509**	0.704**	0.258	0.436**
	(0.223)	(0.293)	(0.156)	(0.203)	(0.235)	(0.311)	(0.169)	(0.172)
Certain	0.294	0.406	0.00233	0.210	-0.0760	0.147	0.0610	0.257
	(0.224)	(0.356)	(0.149)	(0.258)	(0.237)	(0.360)	(0.166)	(0.274)
Algorithm × certain		-0.220		-0.378		-0.400		-0.357
		(0.491)		(0.296)		(0.501)		(0.337)
Periods 1 to 5	0.320***	0.321***	0.349***	0.350***	0.309***	0.311***	0.320***	0.322***
	(0.0968)	(0.0973)	(0.0493)	(0.0492)	(0.0578)	(0.0572)	(0.0420)	(0.0410)
Periods 20 to 25	-0.252***	-0.254***	-0.160***	-0.163***	-0.395***	-0.398***	-0.322***	-0.325***
	(0.0841)	(0.0841)	(0.0555)	(0.0562)	(0.0798)	(0.0806)	(0.0483)	(0.0476)
Supergame							0.300***	0.301***
							(0.0647)	(0.0633)
Constant	-1.122***	-1.184***	-0.687***	-0.792***	-0.625***	-0.737***	-1.103***	-1.206***
	(0.175)	(0.169)	(0.159)	(0.185)	(0.186)	(0.183)	(0.147)	(0.119)
Obs.	7,416	7,416	6,180	6,180	6,489	6,489	20,085	20,085

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.5: Treatment effects, probit model.

Robustness Check for Impact of Lab Location and COVID-19 Pandemic

	Supergame 1		*Supergame 2*		*Supergame 3*		*All*	
Algorithm	-0.0225	0.00809	0.108**	0.178*	0.185**	0.255	0.0847	0.140
	(0.0528)	(0.0964)	(0.0526)	(0.0959)	(0.0813)	(0.171)	(0.0516)	(0.0912)
Certain	0.0706	0.101	0.000116	0.0727	-0.0292	0.0453	0.0166	0.0744
	(0.0542)	(0.119)	(0.0515)	(0.104)	(0.0833)	(0.154)	(0.0523)	(0.0982)
Algorithm x Certain		-0.0593		-0.140		-0.142		-0.111
		(0.166)		(0.132)		(0.237)		(0.142)
Corona[a]		0.00746		0.0185		-0.00497		0.00684
		(0.0898)		(0.0702)		(0.138)		(0.0754)
Laboratory[b]		0.00513		-0.0118		0.0184		0.00421
		(0.0824)		(0.0625)		(0.114)		(0.0640)
Periods 1 to 5	0.0867***	0.0867***	0.129***	0.129***	0.116***	0.116***	0.110***	0.110***
	(0.0234)	(0.0234)	(0.0177)	(0.0172)	(0.0199)	(0.0198)	(0.0133)	(0.0132)
Periods 20 to 25	-0.0524***	-0.0524***	-0.0522***	-0.0522***	-0.129***	-0.129***	-0.0821***	-0.0821***
	(0.0159)	(0.0159)	(0.0160)	(0.0158)	(0.0292)	(0.0289)	(0.0108)	(0.0107)
Supergame							0.0968***	0.0968***
							(0.0216)	(0.0211)
Constant	0.133***	0.111	0.245***	0.207**	0.268***	0.224	0.120***	0.0859
	(0.0405)	(0.0952)	(0.0518)	(0.0917)	(0.0625)	(0.137)	(0.0401)	(0.0838)
Obs.	7,416	7,416	6,180	6,180	6,489	6,489	20,085	20,085
R^2	0.025	0.027	0.029	0.034	0.057	0.063	0.062	0.066

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.6: Laboratory location and COVID-19 effects, linear probability model.

[a]Corona = 1 if the session was conducted under hygiene rules of the pandemic.
[b]Laboratory = 1 if the session was run in Bonn.

Instructions

Welcome to the experiment

Thank you for your participation in this experiment. Please read the instructions carefully. For your participation in today's experiment, you will receive 5 euros. During the experiment, you will have the opportunity to earn an additional amount of money. The additional amount will depend on your decisions and the decisions of the other participants. A short questionnaire will follow the experiment. From now on, please stop any conversations with your neighbors. Turn off your cell phone and remove everything from your table that you do not need for the experiment. If you have any questions, please raise your hand and we will answer them one-on-one.

Instructions

In this experiment, you will take the role of a firm in a market. Each market consists of three firms. Each of the three firms is represented by a human participant.

> **Human_Certain**
>
> The three participants decide for themselves the price for which they want to sell their goods for their firm and are paid the profit their firm makes in cash at the end of the experiment.

All firms offer 24 units of a comparable good with no cost of production, and with 24 consumers demanding one unit of the good. Consumers' willingness to pay for a good ranges from 1 to 100 ECU (Experimental Currency Units), where 1,000 ECU = 1 Euro. At the beginning of each period, all firms have the option to set a high price (100 ECU) or a low price (60 ECU) for their good. The company which alone has set the lowest price serves the entire demand. All other companies will not sell any of their units. If several companies have set the same lowest price, the demand is divided equally among them. The following three examples illustrate the mechanism of the market:

	Both competitors choose the high price	One competitor chooses the high price, the other competitor chooses the low price	Both competitors choose the low price
You choose the high price (100 ECU)	800 ECU	0 ECU	0 ECU
You choose the low price (60 ECU)	1440 ECU	720 ECU	480 ECU

Example 1

You are firm A and you decide to charge a high price for the units of your good (100 ECU). Firm B makes the same decision, whereas C sets a low price (60 ECU). Firm C now has the cheapest sales offer and will serve the complete demand. Accordingly, firm C will earn (60 ECU $*24$ units sold $=$) $1,440$ ECU. Firms A and B will not sell any units and will therefore earn 0 ECU in this period.

Example 2

You are firm A and you decide to charge a low price for the units of your good (60 ECU). Firms B and C make the same decision. Firms A, B, and C have now all made the lowest sales offer and will each sell 1/3 of the demand, thus $24/3 = 8$ units of their goods. Accordingly, each firm will earn (60 ECU $*8$ units sold $=$) 480 ECU.

Example 3

You are firm A and you decide to charge a high price for the units of your good (100 ECU). Firms B and C make the same decision. Firms A, B, and C have now all made the most favorable sales offer and will each sell 1/3 of the demand, thus $24/3 = 8$ units of their goods. Accordingly, each firm will earn (100 ECU $*8$ units sold $=$) 800 ECU. Thus, your earnings depend on your own and the other firms' pricing decisions. This results in the following profit table for you:

After all the firms have made their choice, you will be informed about the chosen prices of the other two firms and about your profit.

Periods and rounds

In total, you will play at least 20 periods with the other two firms. Random chance will decide whether or not additional periods will be played in the sequel. With a probability of 70% the round will continue with another period; with a probability of 30% the round will end. The round continues until random chance determines the end. In each period of a round, you will be playing with the same participants in a market. At the end of these $20 + x$ periods, all participants are randomly assigned to new markets and a new round begins. The three participants in the new markets will then stay together again for $20 + x$ periods.

In total, you will play three rounds of $20+x$ periods. After three rounds, the experiment ends and a short questionnaire follows.

Human_Uncertain and Algorithm_Uncertain

Market decisions by algorithms

In your markets, at least two participants decide for themselves the price for which they want to sell their goods for their firm and are paid the profit their firm makes in cash at the end of the experiment. **With 50% probability, the decisions for the third firm will also be made by one participant. Also with 50% probability, the third firm will be equipped with an algorithm in all rounds, which will make the necessary pricing decisions for the participant.** In this case, the participant does not make any decisions, but still gets paid in cash the profit that her firm makes.

Algorithm_Certain

Market decisions by algorithms

In your markets, two participants decide for themselves the price for which they want to sell their goods for their firm and are paid the profit their firm makes in cash at the end of the experiment. **The third firm will be equipped with an algorithm in all rounds, which will make the necessary pricing decisions for the participant.** In this case, the participant does not make any decisions, but still gets paid in cash the profit that her firm makes.

Payout

For your payout, one of the three rounds will be randomly selected. The ECU earned there will be paid to you additionally in euros.

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ISSN 2190-992X (online)
ISBN 978-3-86304-391-9