Delegate Pricing Decisions to an Algorithm? Experimental Evidence

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Abstract

In a market experiment, we analyze the propensity of participants to delegate their pricing decisions to an algorithm. The optional algorithm is the result of extensive (offline) Q-learning simulations. It is capable of tacit collusion and, when playing against itself, is more collusive than humans. We compare three settings. In the baseline, both participants set prices manually. In one treatment, participants can fully delegate pricing to the algorithm. In another treatment, they receive algorithmic recommendations but retain the option to override them. Delegation rates range from 45% to 86%, with participants delegating significantly more when they can override the algorithm's decisions. In both settings, the price is lower than in the baseline variant where two humans compete, and it does not increase in later supergames. These results suggest that while self-learning pricing algorithms can be highly collusive, their impact depends on human decision-making. If participants retain control, the algorithm may even foster competition rather than collusion. This highlights the need to study human-algorithm interactions rather than viewing algorithms in isolation.

Keywords: Algorithm aversion, collusion, experiment, human-machine interaction, Q-learning

JEL Codes: C90, D43, L12

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1 Introduction

Algorithms are becoming an integral part of everyday life, performing tasks such as driving cars, analyzing medical images, managing financial portfolios, and curating social media content. Many of these algorithms are self-learning and make decisions autonomously, which often leads to concerns about a lack of transparency, making them seem like "black boxes" to the humans they are meant to support.

Possibly (also) due to the lack transparency, recent research has shown that aversion to algorithms may limit their use. Experiments show that people avoid algorithmic advice even when the algorithm is superior to humans (Dietvorst et al., 2015). Only when human decision makers can retain some control over algorithmic decisions are they more inclined to accept decisions of algorithms (Dietvorst et al., 2018).

Both of these issues—the increasing prevalence of algorithms and the potential human reluctance to accept their advice—are relevant in markets where pricing algorithms play a major role. While pricing algorithms are also used by traditional businesses, such as gas stations (Assad et al., 2024) or supermarkets (Competera, 2024), they are rather relevant in the growing e-commerce sector (Chen et al., 2016b). The majority of online enterprises monitor their competitors' prices, with two-thirds using algorithmic pricing software to do so (EU Commission, 2017). Importantly, while the share of online businesses using algorithms is high, it is not complete.

In markets, price algorithms can offer benefits to consumers,[1] but they also carry the risk of facilitating tacit collusion. Research by Calvano et al. (2020) and Klein (2021) shows that self-learning algorithms are capable of learning to collude in repeated pricing scenarios. These algorithms can even develop strategies that include punishments to deter deviations from cooperative behavior. As a result, price algorithms may engage in tacit collusion.

Our paper investigates the willingness to use a pricing algorithm in a laboratory experiment. In a market environment with price competition, participants have the option of using a pricing algorithm (say, like a seller on Amazon Marketplace).[2] The algorithm they can choose is a self-learning algorithm that has learned to cooperate against itself in Q-learning simulations, similar to those in Calvano et al. (2020) and Klein (2021). The instructions of the experiment implicitly demonstrate that the algorithm performs superior and cannot be exploited. In the first treatment, choosing to adopt the algorithm means fully delegating all pricing decisions to it. In

[1]Algorithms are adept at processing large volumes of data related to competitors and customers, allowing for dynamic price adjustments. They also help maintain consistent pricing strategies and can quickly react to market changes. These efficiency gains have the potential to benefit consumers in the long run.

[2]On platforms such as Amazon, sellers can choose between rule-based algorithms, which follow predefined pricing rules, and more advanced algorithms, which dynamically adjust prices based on market conditions. These tools are available either directly from Amazon, through its Automate Pricing feature, or from third-party providers such as BQOOL.

doing so, participants effectively commit to tacit collusion: If all players decide to adopt the algorithm, they will achieve maximum joint profits. However, algorithm aversion may preclude this. In a second treatment, the algorithm merely gives advice which price to select. Here, participants can override the algorithm's advice, and the results of Dietvorst et al. (2018) suggest that subjects are more inclined to choose algorithmic advice.[3]

In addition to studying algorithm aversion in a novel environment and the implications for tacit collusion, our work also touches on the issue of human-algorithm interaction. In our experiment, some participants will inevitably use the algorithm and others will not, leading to "hybrid" markets where humans and algorithms interact. While we do not inform subjects when their counterparts are using an algorithm, subjects who retain decision control may explore whether this is the case or even (mistakenly) try to exploit the algorithm. This is clearly also a problem in the field in online markets where the proportion of firms using algorithms is high but (as seen) incomplete, leading to human-algorithm interactions.

Our research questions are as follows. First, will subjects use a pricing algorithm? Second, are participants are more inclined to do so when the algorithm merely recommends prices (as opposed to a full delegation of decision power). Third, what are the implications for tacit collusion? And fourth, how do humans interact with algorithm rivals?

Our results are as follows. As expected, the nonbinding algorithm is chosen more often than the binding one. While participants do choose the algorithm rather often, they do so at a decreasing rate. Although the algorithm is capable of perfectly monopolizing the market, our baseline treatment where two humans interact, exhibits the highest prices.

2 Related literature

Our research bridges two strands of the experimental literature, one related to competition and algorithmic pricing and the other on algorithm trust and delegation. Simulating decision-making scenarios where participants can delegate price decisions to algorithms can enrich the existing literature.

Dietvorst et al. (2015) study algorithm aversion. The study demonstrates that participants tend to have a negative bias towards algorithms, particularly after witnessing their performance, even when the algorithms outperform humans. The researchers explain that individuals tend to lose trust in algorithms more quickly

[3]In practice, both full delegation and algorithmic recommendations are commonly used. For instance, Huelden et al. (2024) and Li et al. (2021) report on a pricing system at a large e-commerce firm in which algorithms are fully responsible for pricing decisions by default, while humans can only intervene to overwrite them. On the other hand, for instance Garcia et al. (2024) describe algorithms for hotel room pricing that only serve as recommendations to human pricing managers. As such, both delegation treatments are also relevant from a practical perspective.

than in humans, even when both make comparable mistakes. Dietvorst et al. (2018) highlight algorithm aversion, wherein participants prefer modifying algorithmic outcomes, indicating a desire to retain control. This preference for modifiability reduces algorithm aversion, underscoring the importance of allowing stakeholders some control over algorithmic decisions.

Assad et al. (2024) provides empirical evidence of how algorithmic pricing can influence market collusion dynamics in the retail gasoline market. The research shows that adopting algorithmic pricing software leads to a significant increase in profit margins in competitive markets only when it is adopted by all firms. However, the adoption of the algorithm by only some of them does not affect average market-level margins or prices when compared to similar markets where no firms adopt it.

Regarding the experimental literature, Calvano et al. (2021) and Klein (2021) both study the effect of Q-learning algorithms on the strategic behavior of firms through computational experiments and find that throughout repeated games, algorithms' strategies converge to collusive outcomes including supra-competitive prices and profits, and punishment for rival price reductions.

Moreover, Hunold and Werner (2023) explores the collusive and competitive effects of algorithmic price recommendations. They find that sellers condition their prices with algorithm recommendations and that the type of algorithm induces different results. An algorithm with a soft punishment strategy has a pro-competitive effect, and an algorithm that recommends a sub-game perfect equilibrium strategy expands the range of market outcomes to include more collusive cases.

Normann and Sternberg (2023) and Werner (2021) investigate the level of competition in markets where decision-making is delegated to algorithms. Their findings reveal that the mere presence of algorithms results in higher prices compared to scenarios involving only human decision-makers. In hybrid markets, firms utilizing algorithms experience lower profitability, suggesting a reluctance of human participants to collude with algorithms.

TODO cite those guys Schauer and Schnurr (2023) TODO – paper quite close to us more more focused on live learning of the algorithm

3 Experimental Design

3.1 Market game and equilibria

We use the Bertrand market proposed by Dufwenberg and Gneezy (2000) in a static environment and commonly used in collusion experiments (see, for example, Fonseca and Normann, 2012). The market consists of two firms producing a homogeneous good facing perfectly inelastic demand. They have no (marginal) cost of production. The firms' action sets are the integer prices $\{0, 1, 2, ..., 5\}$. Depending on the treatment, a human or an algorithm may set the price. Total demand is given by

$m = 60$ computerized consumers who are willing to purchase one unit of the good in each round as long as the price does not exceed the maximum willingness to pay, $\bar{p} = 4$. Consumers buy the good from the firm offering the lowest price. The market is divided equally if both firms offer the same price in a given period. This market environment is the same across all experimental treatments.

Subjects play five infinitely repeated supergames using the above Bertrand duopoly as the stage game. In each period, there is a 95% probability that the supergame will continue for another round, mimicking the infinite time horizons and discount factors inherent in repeated-game analyses as first implemented by Roth and Murnighan (1978). This information is known to the participants. Compared to other experiments (see the meta study of Dal Bó and Fréchette, 2018), the continuation probability is relatively high. This was done to maintain comparability to studies that investigate the collusive potential of self-learning algorithm where simulations are typically conducted with a continuation probability of at least 0.9. In order to have experimental sessions with the same supergame lengths, the round numbers are pre-drawn with a random number generator and are not provided to participants.

The equilibria of the market game are as follows. In the one-shot game, the set of pure-strategy Nash equilibrium prices is $\{0, 1, 2\}$. In the repeated game, more subgame perfect equilibria can occur. Next to the static Nash equilibria, both firms charging a price of 3 or 4 are subgame perfect equilibria with grim trigger strategies. The collusive price of 4 maximizes the joint profits: When both firms charge this price, the profit is $4 \times 30 = 120$ each. The deviation profit is $3 \times 60 = 180$ and the Nash threat profits for $p^{NE} = 0$ (the most severe credible punishment) are zero. Adhering to the collusive price of 4 is better than deviating if and only if $120/(1 - \delta) \geq 180 \Leftrightarrow \delta \geq 1/3$. Similar calculations for the collusive price of 3 show that adhering is better than deviating if and only if $\delta \geq 1/4$.

We conclude that the prices 0, 1 and 2 can be interpreted as (Nash-)competitive price levels. A price of zero is the severest Nash punishments in the repeated game. Prices 3 and 4 are supra-competitive and may indicate tacit collusion. A price of 5 would imply zero demand, and thus probably indicates an error. The termination probability in the experiment is sufficiently high for tacit collusion to be a subgame perfect equilibrium.

3.2 Treatments

We consider three experimental treatments in which we modify whether and how participants can use the help of an algorithmic pricing agent. We call these treatments Baseline, Outsourcing and Recommendation.

In the Baseline treatment, participants do not have the option of using a pricing algorithm in any way. They set the prices themselves, as in a standard Bertrand experiment.

In the Outsourcing treatment, participants can delegate the pricing decision to the algorithm or play the supergame themselves. This decision is made once, at the beginning of each supergame. If subjects choose the algorithm, they are fully committed to the algorithm's decisions for the entire supergame.

In the Recommendation treatment, subjects can choose to get support from the algorithm, also once at the beginning of each supergame. Unlike Outsourcing, the algorithm's choices are only recommendations. Participants can still set prices as they wish, that is, they can overwrite the recommendation in each round of the supergame.

3.3 Algorithm

We use Q-learning algorithms, a class of reinforcement learning algorithms (Watkins, 1989, Watkins and Dayan, 1992). Q-learning algorithms are designed to solve Markov decision processes with an ex-ante unknown environment. In other words, the algorithm learns everything by itself without being instructed to follow a particular strategy and without having prior knowledge of the market environment. It has the objective to maximize the stream of future discounted rewards. The algorithms learn how to price the product in a given market environment by interacting with other algorithms in a simulated market environment. It is the primary building block of the popular reinforcement learning algorithms that learn to play video games or beat humans at the game of Go (e.g., Mnih et al., 2015, Silver et al., 2016). Also, there is evidence that companies use those algorithms for their pricing systems (Liu et al., 2019).

Q-learning has been used to study the behavior of pricing algorithms. Calvano et al. (2020), Klein (2021), Johnson et al. (2020), and others show that those algorithms can learn to collude on non-competitive prices tacitly. A firm that wants to outsource its pricing decision to an algorithm might be incentivized to use such algorithms as it can facilitate market coordination and thereby increase profits. As such, it is a natural choice for our experiment. We follow the approach by Werner (2021) to train the algorithm. As the market environment we consider is the same as in this paper, also the algorithms converge to the same collusive outcomes. Thus, we consider the exact same algorithm in our experiment.

The algorithm learns a win-stay lose-shift strategy (WSLS) or perfect tit-for-tat, popularized for the iterated prisoners dilemma by Nowak and Sigmund (1993). It cooperates at the monopoly price if both firms picked the monopoly in the previous round. If some firm deviates, it punishes this deviation by playing the stage game Nash equilibrium of $p^{NE} = 1$. If both firms play the Nash equilibrium in a given round, the algorithm reverts to the monopoly price of $p^M = 4$. For any other combination of prices from the previous period, it chooses the stage game Nash equilibrium price of 1 again.[4]

While humans rarely adopt win-stay lose-shift strategies in strategically similar environments (see, for instance, Wright, 2013, Dal Bó and Fréchette, 2019), the strategy has several advantages. By adopting it, firms gain a tool that actively foster collusion rather than simply imitating the behavior they would otherwise follow. First, the algorithm punishes deviations and makes collusion incentives compatible. Competitors are better off colluding with the algorithm than deviating in the current round for some immediate additional profit, but at the expense of punishment afterward. Furthermore, the algorithm is forgiving. Strategies like Grim Trigger can also make collusion incentive compatible, but they can never return to the collusive price level. This outcome is undesirable for an algorithm in a pricing environment because competitors may explore the action space, and a trigger strategy would perceive such exploration as a deviation. While the algorithm has these advantages, it is important to highlight that they arise from the learning process of the algorithm and were not designed by us as the experimenter.

The algorithm is the same for all participants, and we only used the limiting strategy after convergence. In other words, it does not learn during the experiment but uses the strategy it has learned during the training. Therefore, the algorithm's behavior remains consistent throughout the experiment.

While in practice, the algorithms used by competing firms do not necessarily have to be the same, it can often be the case. For instance, Harrington (2022) argues that pricing algorithms are frequently supplied by a common intermediary, meaning that competing firms often rely on the same or very similar algorithms. As such, the setup of firms using the same algorithm reflects real-world scenarios, especially in e-commerce markets where such third-party algorithm providers commonly operate. Moreover, the strategy learned by the pricing algorithm is a type commonly learned by reinforcement learning algorithms, as shown by Kasberger et al. (2023), Schaefer (2022), Barfuss and Meylahn (2022). Hence, it is reasonable to assume that firms using reinforcement learning-based algorithms ultimately rely on algorithms that share a similar strategy.

3.4 Procedures

The experiment was programmed in oTree (Chen et al., 2016a), and a total of 19 sessions were conducted. Of these, thirteen were conducted at the DICELab in

[4]As the algorithm triggers only a one-period punishment (which is less severe than the grim trigger analyzed above), we need to demonstrate that colluding with the algorithm, or collusion between two algorithms, is also a subgame perfect Nash equilibrium. For a collusive price of 4, this is the case if and only if it is not profitable to deviate in the current period and jointly play the stage game Nash equilibrium for one period afterwards. Formally, this condition is fulfilled if and only if $120 + \delta 120 \geq 180 + \delta 30 \Leftrightarrow \delta \geq 6/9$. Similarly, for the collusive price of 3, colluding with the algorithm is subgame perfect if and only if $\delta \geq 1/2$.

Düsseldorf, and six sessions at PLEx in Potsdam.[5] Overall, 100 participants were assigned to each treatment, totaling 300 participants in the experiment.

At the beginning of the session, participants receive the instructions on the computer screen. The instructions and additional information are also available at any time during the experiment. Participants in the Outsourcing and Recommendation treatments receive information about the algorithm at the beginning of the session and at each supergame. After reading the instructions, participants answer a series of control questions. If a participant gives an incorrect answer three times, we provide the correct answer and explain the question.

The sessions in all treatments had five supergames. At the beginning of each session, two participants are matched for the duration of the supergames. At the start of the next supergame, participants are randomly rematched into new markets within a matching group of ten participants. The random rematching reduces the likelihood of potential reputation effects across supergames.

Participants know that the algorithm is self-learned and that its objective is to maximize the participant's long-run profit. To further align expectations on the possible performance of the algorithm, participants receive a comprehensive overview of the algorithm's past performance in different market compositions from the previous experiment by Werner (2021).[6] The algorithm's past performance is presented as a 2×2 payoff matrix, showing the outcomes when no firm, one firm, or both used the algorithm.

Right after the control questions, all participants play three trial supergames with a total of 15 periods against the algorithm. This allows every participant to understand how a supergame works and, in the case of participants of treatments Outsourcing and Recommendation, also to comprehend the algorithm strategy better.[7] These three simulation supergames were not payoff relevant.

At the end of each period, participants receive information about prices and profits. At the end of each supergame, we elicit participants' beliefs in Recommendation and Outsourcing. Participants are asked to state how much confidence - in percentages - they have that their opponent used the pricing algorithm in the previous supergame. They can receive an additional reward for guessing correctly.

[5] We aimed to balance session sizes across treatments. At DICELab, we conducted eight sessions with 20 participants each, but due to no-shows, the ninth session in Outsourcing was split into two smaller sessions of 10 participants, resulting in a total of eight 20-participant sessions and five 10-participant sessions (instead of three). At PLEx, we ran three sessions with 20 participants and three with 10, balanced across treatments.

[6] As the experimental design in Werner (2021) differs in that participants were assigned to a condition and did not have the choice to adopt an algorithm, we inform our participants of this fact. We also emphasize that past performance is not indicative of future profits, particularly because the use of the algorithm was predetermined, unlike having the additional choice of delegating to the algorithm initially.

[7] To keep the learning experience the same across treatments, also in the Baseline treatment, participants engage in the simulation against the algorithm. While in Recommendation and Outsourcing we explicitly tell participants that they play against the algorithm, we do not provide those details in Baseline to avoid any confusion.

We incentivize belief elicitation using the binarized scoring rule (Hossain and Okui, 2013) with a framing similar to Danz et al. (2022).

At the end of the session, participants answer an end-of-study survey regarding demographics and algorithm trust. They are then informed of the reward they earn in euros, including their profit in one selected supergame, the correctness of their belief in algorithm use and a show-up fee, and information about how it is computed.

3.5 Hypotheses

Participants are free to choose whether to adopt an algorithm. While adopting the algorithm in OUTSOURCING and following the algorithm's advice in RECOMMENDATION leads to the joint profit maximum, this is only the case if both players do so. Thus, the adoption decision is risky in period one and we expect that some participants will delegate while others will not.

Previous experiments have shown that algorithm trust is increased when participants have some control over the final decision (Dietvorst et al., 2018). Furthermore, in OUTSOURCING, using the algorithm is possibly associated with some cost. While the algorithm can foster collusion, participants lose the ability to implement their own strategy which might be important to them. Conversely, using the algorithm is costless in RECOMMENDATION. Participants can choose a price different from the one the algorithm recommends. Furthermore, besides recommending them a pricing strategy, it also allows them to anticipate how their competitor might behave if they also use the algorithm. Therefore, participants are more likely to delegate to pricing algorithms when they can override the algorithm's pricing decision than when they must completely delegate it.

Hypothesis 1. *Participants are more likely to delegate in* RECOMMENDATION *than in* OUTSOURCING.

Importantly, the algorithm has the potential to foster collusion by playing a deterministic trigger strategy with one period punishment. The algorithm cannot be exploited either (any strategy other than colluding with $p = 4$ yields a strictly lower profit). Therefore, in treatments where participants can delegate the price decision to the algorithm, we expect prices to be higher than those in the baseline treatment.

Hypothesis 2. *In* OUTSOURCING *and* RECOMMENDATION, *prices are higher compared to* BASELINE.

An open question is whether the ability to override the algorithms leads to higher prices (RECOMMENDATION) compared to fully delegating pricing decisions to an algorithm (OUTSOURCING). On the one hand, we hypothesize that participants delegate more when they can override the pricing decision. On the other hand, conditional on the decision to use an algorithm, the opportunity to override the recommendation of the collusive algorithm may lead to lower market prices compared to fully outsourcing the pricing decision. As an exploratory research question, we ask which of these two effects dominates.

Further, comparison between and across treatments allows us to determine whether the level of commitment to the algorithm decision comes into play when deciding whether to use it. While the Baseline treatment includes only human agents, in the case of Outsourcing and Recommendation, there might exist three types of markets: fully human markets (HH), fully algorithmic markets (AA) and hybrid markets (AH). Comparison between market types helps determine whether one of them is more collusive. The comparison across treatments might also be affected by the uncertainty of human agents about the type of agent they are facing. Thus, at the end of each supergame, participants assigned to the Outsourcing and Recommendation treatments are incentivized to state if they believe their opponent used the algorithm.

4 Results

4.1 Algorithm adoption

Figure 1 shows the frequency with which participants delegate their decisions to the algorithm ("algorithm adoption") in Recommendation and Outsourcing across the five supergames.[8] Delegation rates range from 45% to 86%, depending on the treatment and supergame, indicating substantial adoption of the algorithm. Algorithm adoption rates are consistently higher in Recommendation compared to Outsourcing. While we observe high adoption rates at the start of the experiment, these decline, particularly in Outsourcing. Delegation rates exhibit a negative trend across supergames in both treatments, although with a sharper decline in the first three supergames of Outsourcing.

[8]Recall that subjects make a single delegation decision at the beginning of each supergame.

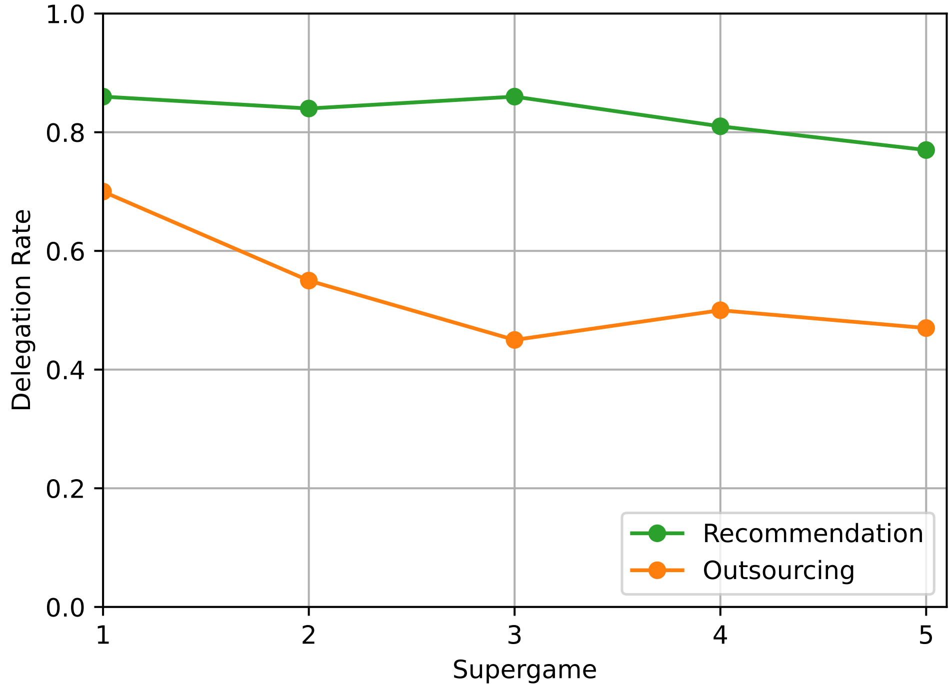

Figure 1: Algorithm adoption rates across supergames

Table 1 presents the results of linear regressions that show the statistical significance of these findings. RECOMMENDATION has significantly higher adoption rate than OUTSOURCING (represented by the constant). The data thus reject the null hypothesis and are consistent with Hypothesis 1, that participants are more likely to adopt an algorithm for pricing decisions in the RECOMMENDATION treatment than in the OUTSOURCING treatment. This pattern holds consistently across all supergames. In regression (3), the coefficient supergame applies to OUTSOURCING and is significant, while the time trend in RECOMMENDATION is also significant (Wald test, Supergame + RECOMMENDATION $\times$ Supergame, $p < 0.05$).

Result 1. Participants choose the algorithm frequently, but decreasingly across supergames. The adoption rate is higher in RECOMMENDATION than in OUTSOURCING.

Table 1: Algorithm Adoption by Treatment

	Algorithm Adoption		
	(1)	(2)	(3)
Recommendation	0.29***	0.29***	0.20***
	(0.05)	(0.05)	(0.06)
Supergame		−0.04***	−0.05***
		(0.01)	(0.01)
Recommendation × Supergame			0.03**
			(0.01)
(Intercept)	0.53***	0.64***	0.69***
	(0.04)	(0.05)	(0.04)
Sub-sample	All	All	All
Num. obs.	1000	1000	1000
Num. cluster	20	20	20
R^2	0.10	0.11	0.11

Data restricted to Outsourcing and Recommendation treatments. Results are based on linear regression with clustered standard errors at the matching group level. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Figure 2 illustrates how market composition varies depending on whether none, one or both participants adopt the algorithm ("market type"). The right panel presents the data for Recommendation and the left panel for Outsourcing. We have fully algorithmic (AA), mixed human-algorithm (AH), and fully human (HH) markets. In Outsourcing, 92% of markets in supergame 1 had at least one algorithm present—48% were fully algorithmic, while 44% were mixed. By supergame 5, this share declined to 70%, with fully algorithmic markets decreasing by half to 24%, while mixed markets increased slightly to 46%, resulting in an increase in fully human markets from 8% to 30%. In contrast, in Recommendation, at least one algorithm was present in most markets. In supergame 1, 72% of markets were fully algorithmic, while 28% were mixed. By supergame 5, the share of fully algorithmic markets declined to 62%, mixed markets rose to 30%, and fully human markets increased to 8%. In Recommendation, there are 250 markets, but only five were fully human, one in supergame 2 and four in supergame 5.

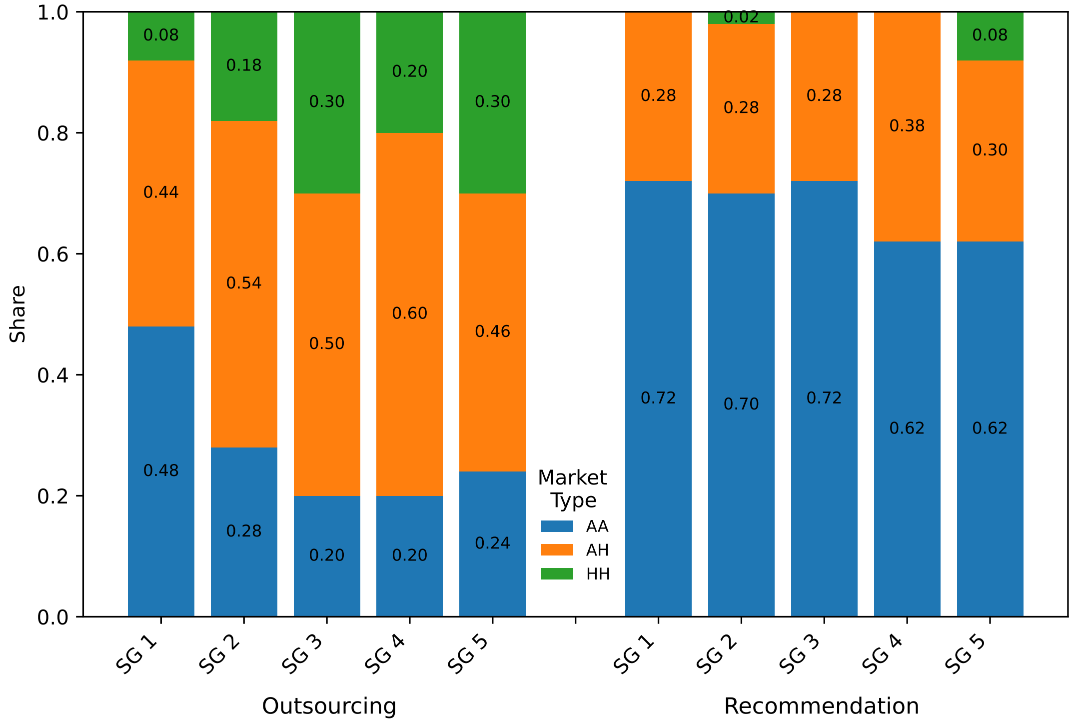

Figure 2: Distribution of market types across treatments and supergames.

4.2 Prices

4.2.1 Market prices across supergames and treatment comparison

Figure 3 presents the average market price across all rounds, separately for each supergame and treatment.[9] Average market prices range from 2.2 to 3.2, depending on the treatment and supergame. Prices in BASELINE are higher than in the other two treatments, except in the first supergame, and market prices in OUTSOURCING are higher than in RECOMMENDATION.

Across supergames, market prices increase in the BASELINE treatment ($\beta = 0.16$, $p < 0.01$, OLS)[10], suggesting a trend toward greater cooperation as participants learn over time. In contrast, average market prices in the OUTSOURCING and RECOMMENDATION treatments fluctuate across supergames, with an overall negative time trend across supergames ($\beta = -0.12$, $p < 0.05$, OLS) in OUTSOURCING, and no statistically significant trend ($\beta = 0.05$, $p > 0.1$, OLS) in RECOMMENDATION.

The regressions in Table 2 analyze treatment differences. Regression (1) confirms that the average market price in BASELINE is significantly higher than in RECOMMENDATION ($p < 0.01$) and not significantly different from OUTSOURCING. These results remain robust to controlling for supergame length in regression (2). In supergame 1, market prices in OUTSOURCING are significantly higher than in BASELINE while prices in RECOMMENDATION are significantly lower, see regression

[9]The market price is the lower of the two prices.

[10]See Table 5 in the Appendix for full linear regression results.

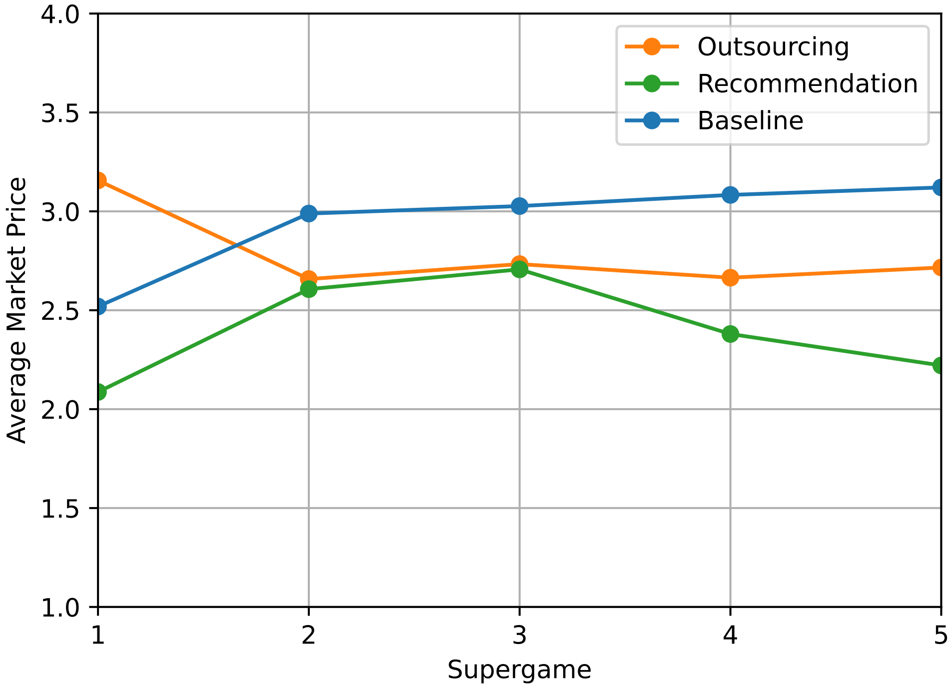

Figure 3: Average market price across supergames

(3). By supergame 5, this pattern is reversed: As shown in regression (4), there is a significant difference in market prices between BASELINE and OUTSOURCING in supergame 5 ($p < 0.05$). The difference in market prices between OUTSOURCING and RECOMMENDATION is highly significant in the full sample (regression (1), $p < 0.01$, Wald test), weakly significant in the weighted model (regression (2), $p < 0.1$, Wald test), and again highly significant in supergame 1 (regression (3), $p < 0.01$, Wald test).[11] Thus, we find no support for Hypothesis 2 that market prices are higher in algorithm-driven treatments than in BASELINE. The opposite seems to be true.

Result 2. Market prices are higher in BASELINE than in RECOMMENDATION and OUTSOURCING.

[11]These regression results are corroborated by nonparametric tests, here Mann-Whitney U tests. Across all supergames, average market prices in the BASELINE treatment are significantly higher than in the RECOMMENDATION treatment ($p < 0.01$, two-sided MWU), and not significantly higher than in the OUTSOURCING treatment. Similarly, market prices in the OUTSOURCING treatment are higher than in the RECOMMENDATION treatment ($p < 0.01$, two-sided MWU). In the final supergame, market prices in BASELINE remain significantly higher than in RECOMMENDATION ($p < 0.01$, two-sided MWU) and not statistically significantly different from market prices in OUTSOURCING. Further, prices in OUTSOURCING treatment are higher than in the RECOMMENDATION treatment, although this result is only weakly statistically significant ($p < 0.1$, two-sided MWU).

Table 2: Market Prices by Treatment

	Market Prices			
	(1)	(2)	(3)	(4)
Outsourcing	0.18	-0.16	0.64^{***}	-0.40^{**}
	(0.15)	(0.15)	(0.20)	(0.18)
Recommendation	-0.56^{***}	-0.55^{***}	-0.43^{**}	-0.90^{***}
	(0.18)	(0.18)	(0.21)	(0.22)
(Intercept)	2.77^{***}	2.95^{***}	2.52^{***}	3.12^{***}
	(0.08)	(0.08)	(0.11)	(0.11)
Sub-sample	All	All	SG 1	SG 5
Num. obs.	30600	30600	16800	6300
Num. cluster	30	30	30	30
R^2	0.05	0.03	0.10	0.07

Results are based on linear regression with clustered standard errors at the matching group level. Model (2) is weighted by supergame length. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

4.2.2 Market prices across periods

Next, we examine how market prices evolve over the periods of the supergames and we start with the prices in the first round. The algorithm either sets or recommends a price of 4 in the first round for adopters, while participants in the Baseline treatment and non-adopters freely choose their initial price. Figure 4 (top three lines) shows the average first-round prices across supergames. Initial prices are generally collusive (at or above 3) in the algorithmic treatments and also for Baseline in supergames 3 to 5. Prices in the algorithmic treatments are significantly higher than in Baseline in the first supergame ($p < 0.01$, pairwise two-sided MWU). The Baseline treatment exhibits a positive trend in first-round prices across supergames. By the final supergame, first-round market prices converge across treatments, with no statistically significant differences between treatments remaining from supergame 3 onwards ($p > 0.1$, pairwise two-sided MWU).

The three bottom lines in Figure 4 indicate the price change from period 1 to period 2 (that is, the price in period 1 minus the price in period 2). We see that this change is practically zero in Baseline in all supergames, while there is a price drop (between 0.5 and 1 on average, in absolute terms) in the algorithmic treatments. That is, the participants in Baseline manage to maintain the initial price level, while they fail to do so in Outsourcing and Recommendation.

Prices generally decline in the subsequent rounds. For the Outsourcing treatment, the difference between first-round and average market prices is significant in supergames 4 and 5 ($p < 0.05$ and $p < 0.01$, Wilcoxon signed-rank test). For Recommendation, the difference is consistently at least weakly statistically significant (SG1, SG4, SG5: $p < 0.01$; SG2: $p < 0.1$; SG3: $p < 0.05$, Wilcoxon signed-rank test). By contrast, in the Baseline treatment, the gap between first-round and average market prices is less pronounced. Wilcoxon signed-rank tests show no significant difference in early supergames (SG1–SG3: $p > 0.1$) and only weak significance in later supergames (SG4: $p = 0.053$, SG5: $p = 0.083$).

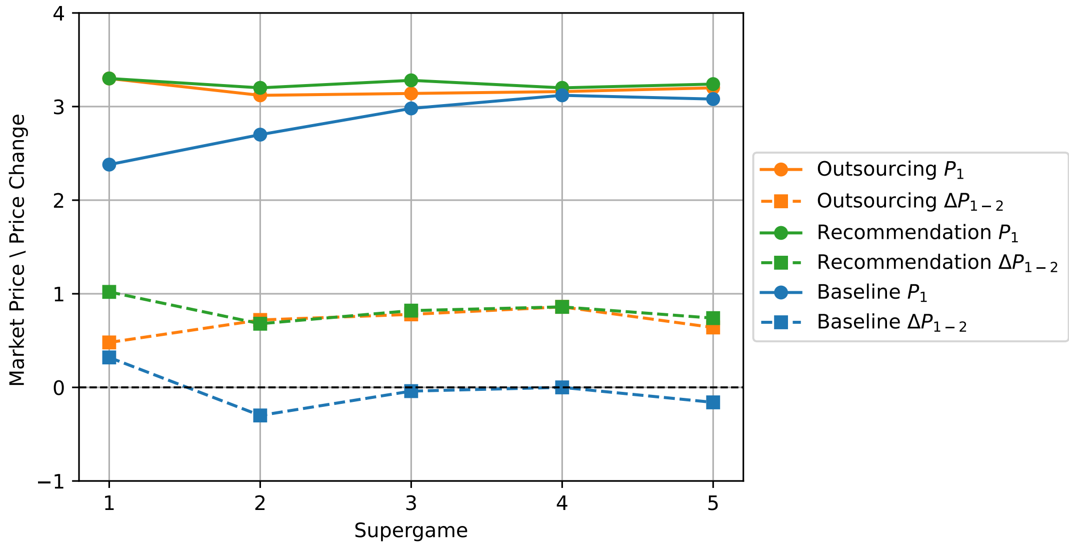

Figure 4: Average First Round Market Price and Difference between First and Second Round

Result 3. While the initial market prices are collusive in all treatments, they remain at that level only in Baseline, and subsequently decrease in Recommendation and Outsourcing.

5 Discussion

The starting point of our discussion of the results is that subjects do actually choose the algorithm, but incompletely so and at a decreasing rate. Contrary to our expectation, prices are higher in the Baseline treatment, where two humans interact without the assistance of an algorithm. While the initial prices in Recommendation and Outsourcing are indeed collusive, they decrease in the following periods.

To put these results into perspective, note that subjects in the algorithmic treatments fail to learn to charge collusive prices across supergames. In infinitely repeated prisoner's dilemma experiments (Dal Bó and Fréchette, 2018), subjects typically improve the cooperation rates when the supergames are repeated. As seen in Figure 3, this is also the case in Baseline but not in Recommendation and

Outsourcing. Also, the participants in the algorithmic treatments fail to maintain stable market prices within supergames (that is, across rounds). Fonseca and Normann (2012) report similar oligopoly Bertrand ("NoTalk") experiments. As in our Baseline treatment, their duopolies have roughly stable prices across the rounds of the supergame, but their oligopolies with $N > 2$ firms exhibit a similar decrease as our algorithmic variants. However, our Recommendation and Outsourcing are duopoly treatments and contain a collusive algorithm. How can we account for these facts?

5.1 Coordination failure in the algorithm choice?

Perfect collusion by following the algorithm could be easy in this experiment, however, both subjects choosing the algorithm is not always the case. When both players choose the algorithm, they would automatically monopolize the market completely in Outsourcing. In Recommendation, they at least have the chance to do so – provided both subjects choose the algorithm and follow its recommendations. As seen in Figure 2, both participants coordinating on the algorithm often fails: in Outsourcing around half of the markets are of the type AH (one algorithm , one human), and in Recommendation this is the case in about 30% of markets.

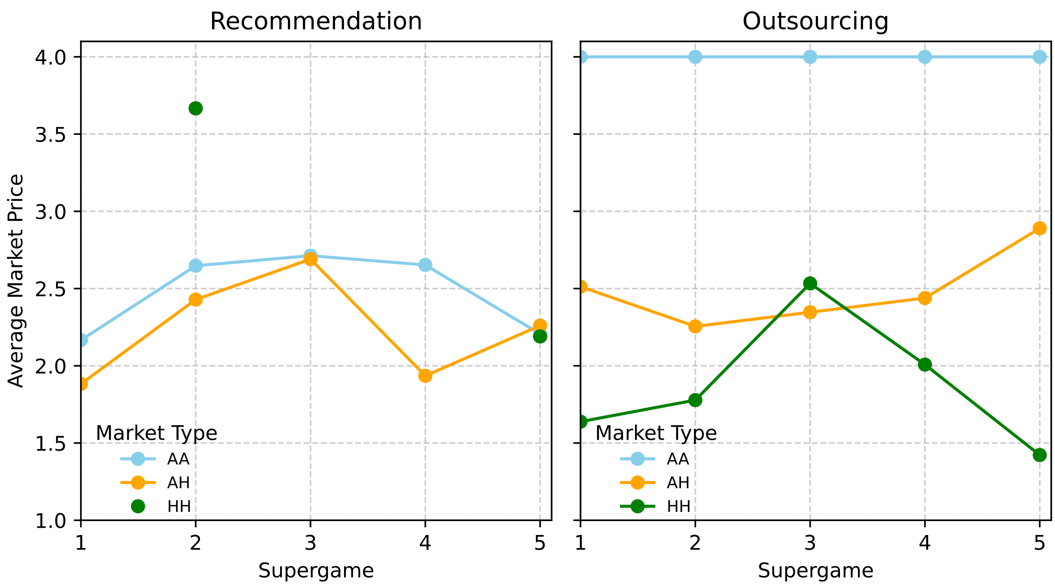

Figure 5: Average market price per market type and supergame

How do such coordination failures affect prices? The right panel of Figure 5 illustrates the average market prices in the Outsourcing treatment across the five supergames, while the left panel presents the same data for Recommendation. We include the human-human (HH) markets also for the Recommendation treatment, but note that there was only one such market in supergame 2 and four in supergame 5 due to higher algorithm adoption rates.

In the Outsourcing treatment, AA markets consistently have a market price of 4, as the algorithm starts at the cartel price and never deviates. Mixed AH markets exhibit lower prices, though they show a moderate increase from supergames 2 to 5. This is surprising, since subjects know how the algorithm works, so they could easily achieve stable collude by charging a price of 4. HH markets have the lowest prices, except in supergame 3. These prices are much below those in Baseline–even though in both cases two humans freely choose prices.

In Recommendation, AA prices have to be (weakly) lower than those in Outsourcing. It is evident, however, that the drop is substantial: The AA prices fluctuate at a level of around 2.5, which is at best moderately collusive. Subjects obviously do not follow the recommended price here. The AH market prices are similar but somewhat below the AA markets.

Table 3, shows how the algorithm adoption choices and subsequent price decisions translate into profits. The table shows the (ex post realized) average profits per round across the five supergames, conditional on the own adoption decision and the adoption decision of the market opponent.

Table 3: Per-period profits, average across five supergames, Outsourcing and Recommendation treatments

Outsourcing

	Algorithm	No Algorithm
Algorithm	120.00, 120.00	57.46, 95.22
No Algorithm	95.22, 57.46	50.34, 50.34

Recommendation

	Algorithm	No Algorithm
Algorithm	68.66, 68.66	60.77, 61.49
No Algorithm	61.49, 60.77	70.00, 70.00

For Outsourcing (top panel of Table 3), we see that choosing the algorithm is even a dominant action (assuming subjects are aware of these payoffs). In the AA markets, the average profit per round is 120, as both players consistently set a price of 4, resulting in shared monopoly profits. Participants facing an algorithm earn an average profit of 95.22 per round, while players using the algorithm achieve only 57.46 per round on average. Profits in AH still exceed those earned in HH markets.

In the Recommendation treatment (bottom panel of Table 3), if both players in a market adopt the algorithm, they earn an average of 68.66 per round. Participants playing with the algorithm against a non-adopting opponent, or vice versa, earn only 60.77 and 61.49 per round, respectively. In HH, profits of 70 are observed, but recall that this figure is based on very few observations.

If we split Table 3 and examine the (ex post realized) average profits per round across the first and last supergame, conditional on the participant's own adoption decision and the adoption decision of their market opponent, as shown in Appendix Table 7, we observe that this pattern holds for OUTSOURCING. In contrast, average normalized profits in RECOMMENDATION converge, showing a limited effect of the adoption decision on realized profits.

Finally, the per-round profit in BASELINE is 83.11. This is higher than the profits in any constellation within RECOMMENDATION, but lower than the profits achieved by participants who adopted an algorithm in AH in OUTSOURCING.

It is important to highlight, however, that while the averages provided in Table 3 are informative, they hide heterogeneity at the individual level. Namely, participants may perceive not using an algorithm as the best response if they are repeatedly exploited by other participants. While exploitation itself can never be profitable compared to cooperation with the algorithm, given that the punishment mechanism of the algorithm makes collusion incentive compatible, participants may still choose this strategy if they believe it is best for them. Duffy et al. (2022) see similar patterns in the context of a repeated Prisoner's Dilemma as even when participants fully understand the algorithm and its strategy (a known Grim trigger opponent), they often fail to follow the optimal strategy. Their design eliminates strategic uncertainty and other-regarding preferences, yet most subjects make systematically suboptimal choices. In such cases, a participant who experiences exploitation can earn significantly less than they would in a human-human market, making non-adoption appear rational from an ex-post perspective.

We also observe this pattern in the data. In Figure 6, we decompose normalized profit by market type. In the first supergame, focusing on the left panel, participants in OUTSOURCING of type AH who adopted an algorithm and played against a human earned substantially less than participants of type HA who did not adopt an algorithm and played against one. Moreover, participants of type AH were outearned by participants in purely human markets in three out of five supergames. If we assume that participants on average form correct beliefs about average outcomes in other markets, this may influence them to view non-adoption as the safer choice, potentially overestimating their ability to reach a collusive outcome without algorithmic assistance. We find limited evidence supporting this interpretation: among the few participants who adopted the algorithm in supergame 1, achieved the maximum payoff, and then chose not to adopt again for the rest of the experiment, only one (ID 13ryqfauqr) out of five managed to reach the maximum payoff in three of the four remaining supergames. The others performed significantly worse (see Appendix Figures 11 and 12). In contrast, the right panel shows that in the RECOMMENDATION treatment, normalized profits were similar across market types, discounting the limited observations in HH markets.

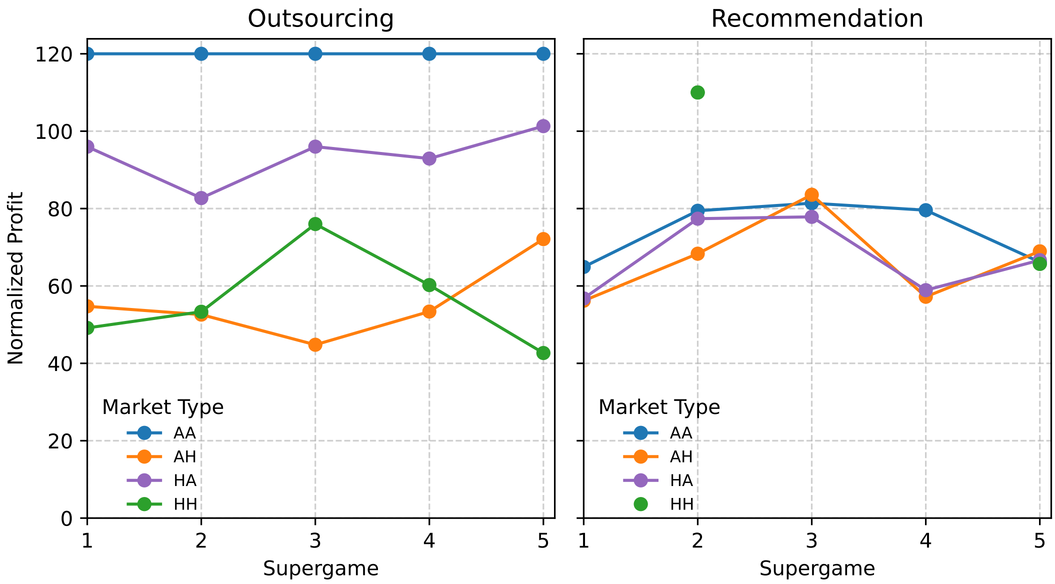

Figure 6: Normalized profit per market type and supergame

To conclude, both subjects failing to coordinate on the algorithm occurs frequently, but can not fully explain our results. Consistent with coordination failure, we find in Outsourcing that the AH markets do a lot worse than the AA markets. But since coordination with the algorithm is straightforward, it remains a puzzle why this is the case. Inconsistent with coordination failure, HH markets in Outsourcing achieve profits below those of Baseline. Also, in Recommendation, mixed AH markets do not perform worse than AA and HH markets.

5.2 Failure to collude in Outsourcing

In the Outsourcing treatment, subjects fail to collude in the AH and HH markets. Why?

In the mixed AH markets, the human players are initially unaware of the nature of their rival. If it is an algorithm, the best response is to collude at the monopoly price. If it is a human, studies in the spirit of Axelrod and Hamilton (1981) and Nowak and Sigmund (1993) suggest that it also profitable to start cooperatively and then behave reciprocally. If subjects behaved this way, they would collude throughout and never find out that the rival player was an algorithm.

However, this is not the case, as only 10 subjects consistently cooperated. More subjects "probe collusion" to see if the rival is an algorithm. Many of them try to exploit the rival by repeatedly undercutting the algorithm, followed by playing 1 to exit the punishment phase. While this strategy is not payoff-maximizing, it does outperform the opponents, as shown in Table 3 as well as Figure 6. Other subjects deviate only once, but, unlike the exploit strategy, resume cooperation when they suspect their opponent has an algorithm.

The exploit strategy accounts for 9 out of 23 AH markets in supergame 5. As shown in Figure 9, this leads to a distinct zig-zag pattern in supergame 5 in the Outsourcing treatment. The prevalence of the exploit strategy, in turn, probably deters subjects from adopting the algorithm in subsequent supergames: The adopter of the algorithm suffers greater losses compared to the exploiter when such exploitation occurs in the Outsourcing treatment, consistent with declining adoption rates in this treatment.

What about the HH markets in Outsourcing? Why do they perform so much worse than Baseline? Of course, subjects in HH markets are also uncertain about their competitors. Here, too, they investigate whether the rival is an algorithm, but with two humans it is apparently more difficult than with the deterministic algorithm to get back to the collusive price of 4. While our treatments do not differ with respect to the price in period 1 (see Figure 4), the price dynamics in periods 2 and 3 already differ.

As shown in Figure 7, which plots the outcome distributions over the first three rounds of supergames 1 and 5, in Baseline we observe a clear pattern of learning and improved coordination. A growing share of markets achieves the collusive outcome (4,4), reaching over 60% by round 3 of supergame 5. While the distribution in round 1 is comparable to the algorithmic treatments, the collusive outcome becomes increasingly dominant. At the same time, punishment outcomes like (1,1), present in about 25% of markets in supergame 1, disappear almost entirely by supergame 5. This is consistent with participants initially experimenting with punishment and gradually converging to stable coordination.

In Outsourcing, the dynamics are different. The share of (4,4) outcomes is relatively stable across rounds and supergames but remains below Baseline, around 50% in supergame 5. The increase in (1,1) outcomes in round 2 is consistent with subjects deviating in round 1 (e.g., leading to (4,3) in 28% of markets), triggering punishment. By round 3, the (4,3) outcome still occurs in 12% of markets, indicating a non-negligible share of exploiters, while some of the round 1 deviators likely either anticipated a probe strategy or employed one themselves.

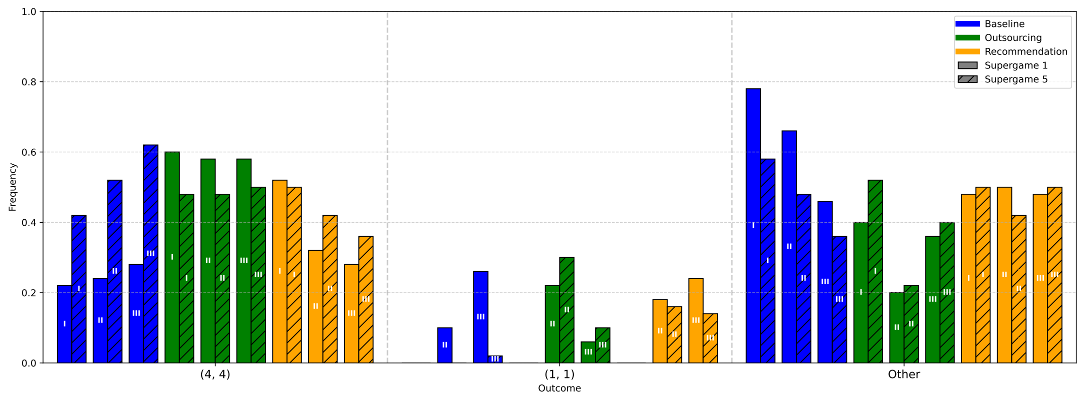

Figure 7: Outcome distribution in the first three rounds across treatments

We argue that this behavior is not driven by myopic decision-making but by a preference for outperforming the opponent. Supporting this, some AH market participants adopted a strategy we label probe into cooperation.

In summary, much of the failure to collude in Outsourcing is likely due to exploring whether there is an algorithm, and when there is, many participants adopt the non-profit maximizing strategy to exploit the algorithm. The persistence of the exploitative patterns is striking given that participants were able to experiment with strategies for free and receive immediate feedback on their profitability during the pre-experiment simulation rounds, and were provided with profit data from previous experiments on algorithm performance at the start of a new supergame, providing insights that might have encouraged more cooperative and profitable decision making. This evidence suggests that some participants prioritize relative performance over absolute payoffs.

5.3 Failure to follow recommendations of the algorithm

We classify the pricing decisions of participants in Recommendation based on whether participants adhered to the recommendation, deviated upward from the recommendation, or deviated downward. Figure 8 illustrates the proportion of each type across supergames. Participants frequently deviate from the price recommendations made by the algorithm, with downward deviations occurring more often than upward deviations. Focusing on supergame 5, only 58% of prices set by participants who adopted the algorithm adhered to the algorithmic recommendation, while 29% of prices set deviated downward, and 14% of prices set constituted upward deviations aimed at reestablishing collusion at higher prices, despite not being recommended by the algorithm at this time.

Note that downward deviations from the algorithm's recommendation can be particularly detrimental regarding prices in subsequent periods. After a deviation from the monopoly price, the algorithm recommends a price of 1 as a punishment. If participants in this punishment period do not follow the recommendation, the algorithm continues to recommend a punishment price of 1. This can exert significant downward pressure on market prices, as downward deviations necessarily mean that the algorithm recommended cooperation, whereas upward deviations translate to not following the punishment recommendation from the algorithm. Consequently, since supergames 2 and 3 exhibit the highest adherence rates to algorithmic recommendations—and adherence is jointly payoff-maximizing—this also translates into the highest average market prices for this treatment, as previously shown in Figure 3. However, as overall market prices remain low, it is necessary to examine how participants deviate from algorithmic recommendations and whether this could explain the lower market prices observed in Recommendation.

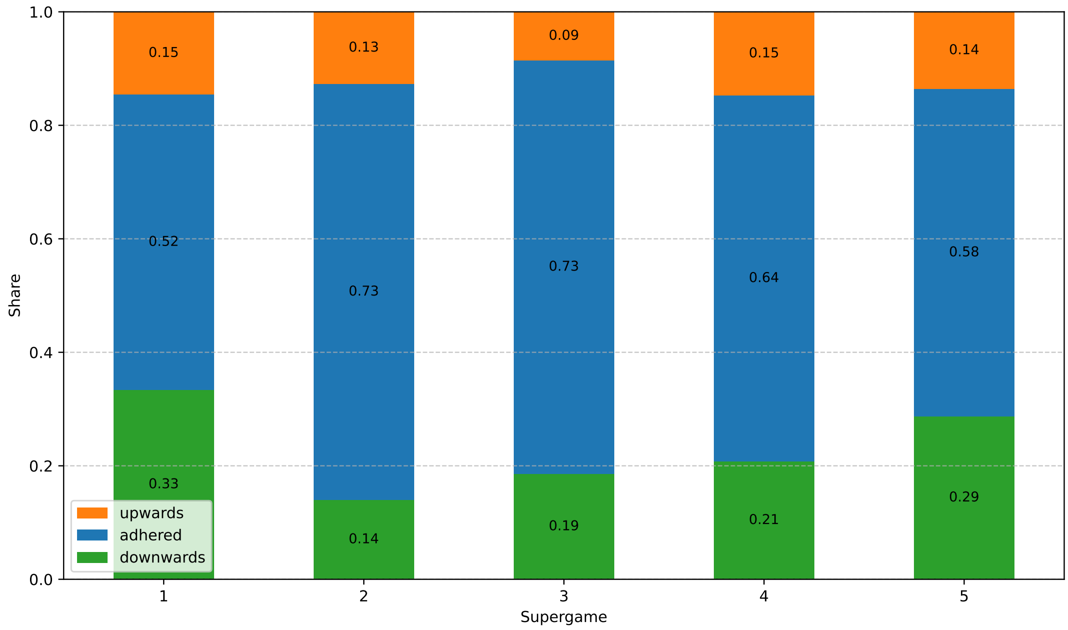

Figure 8: Adherence and Deviations from Algorithmic Recommendations

We split our sample based on the type of algorithmic recommendation—whether the algorithm advised setting a price of 1 as a punishment or a price of 4 to (re-)establish cooperation. This allows for further insights into participant decision-making and the resulting market dynamics. When the algorithm recommends a price of 1, participants frequently deviate upwards, showing reluctance to adhere to the recommended punishment. We observe consistent upward deviation rates ranging from 32% to 43% of all relevant pricing decisions.[12] In contrast, we observe a broader range of adherence rates, varying from 50% to 79%, when the algorithm recommends setting a price of 4. Focusing on supergame 5, this suggests that participants failed to follow the algorithm's recommendation to either maintain or re-establish cooperation in 42% of pricing decisions. Failure to re-establish coordination is particularly evident when examining the first recommendation to return to cooperation following the initial punishment phase of a supergame. While the average duration of this first punishment phase is 2 rounds, the distribution is skewed by markets that remain in punishment for up to 21 rounds. When the algorithm then first recommends re-establishing cooperation after this phase, 60% of participants do not follow the recommendation.

[12]See Appendix Figure 10.

Table 4: Mean Deviations Per Supergame and Overall for Relevant Deviations

Supergame	Recommendation of 1	Recommendation of 4	Difference
1	1.523	-2.550	-1.027
2	1.875	-1.915	-0.040
3	1.727	-1.766	-0.039
4	1.671	-2.229	-0.558
5	1.491	-2.609	-1.118
Overall	1.657	-2.214	-0.557

This effect is further amplified by the magnitude of deviations from the recommended prices, as shown in Table 4. We observe that mean deviations from the recommended price for cooperation exceed those for punishment recommendations. Focusing again on supergame 5, participants, on average, set prices 2.609 below the algorithmic recommendation, while upward deviations average 1.491 above the recommended price of 1. The net difference of -1.118 adds additional downward pressure on prices. Similarly, for supergames 2 and 3, which exhibited the highest market prices for the Recommendation treatment, we observe that not only were adherence rates the highest, but mean deviations from recommended prices were simultaneously the lowest, with absolute differences of just 0.04 in both cases. This suggests that during these supergames, participants followed the recommendations more often, and even when they deviated, the magnitude of upward and downward deviations remained largely balanced, contributing to the observed higher market prices.

Returning to the distribution of outcomes in the first three rounds shown in Figure 7, we observe that in Recommendation, the decline in (4,4) outcomes across rounds suggests that participants are less successful in sustaining collusion. While the drop is more pronounced in supergame 1, the pattern persists in supergame 5. Notably, already in round 1, a considerable share of markets result in deviation outcomes such as (4,3) and (4,2)—25% and 20%, respectively, in the last supergame. This indicates that participants anticipate deviations and adjust their strategy accordingly. The option to override the algorithm appears to introduce strategic uncertainty that undermines stable coordination. Unlike in Baseline, where players gradually learn to cooperate, behavior in Recommendation reflects consistent concerns about deviations.

To conclude, subjects often do not follow the algorithm in Recommendation, resulting in coordination failures. Deviations are more frequent when the collusive price of 4 is suggested, and the magnitude of these deviations is also larger in such cases.

6 Conclusion

Given the increasing importance of pricing algorithms, we ask the research question whether subjects will actually use them? Are participants more inclined to do adopt a pricing algorithm when it merely recommends prices as opposed to a full delegation of pricing decision. Third, what are the implications for tacit collusion? And finally, how do humans interact with algorithm rivals? Following previous results by Calvano et al. (2020) and Klein (2021), we consider the anti-competitive effects of self-learning pricing algorithms when they are a choice. While pricing algorithms can be more collusive than humans and harm competition, the decision to delegate the pricing decision to an algorithm has previously not been considered experimentally.

We consider an indefinitely repeated Bertrand market experiment. We vary across treatments if participants can outsource their pricing decision completely, receive recommendations but can overwrite, or not receive algorithmic support at all.

We find limited evidence that self-learning algorithms still have pro-collusive effects if humans still have the autonomy to decide if they want to delegate their decisions. Market prices are similar to the baseline or the pricing algorithm, which learned highly collusive strategies, even fosters competition and reduces prices.

Our results highlight the heterogeneous effects that pricing algorithms can have on competition. Furthermore, it emphasizes the relevance of human decision-making when discussing the effects of algorithms on markets. As Tsvetkova et al. (2024) examine, studying humans and algorithms as a social system is vital. Studying them apiece may lead to false conclusions. Algorithms rarely exist in a vacuum but are systems designed and deployed by humans. Our results emphasize this as they show that algorithms that are collusive among themselves might not foster collusion if humans remain in charge of those systems but instead lead to more competitive outcomes.

In a future version of this early draft, we plan to extend this analysis and consider the mechanisms that drive the effects to help inform regulation of pricing algorithms and inform policy markers.

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A Results section

Table 5: Market Prices by Treatment Time Trend

	Market Price		
	(B)	(R)	(O)
(Intercept)	2.40***	2.11***	3.23***
	(0.15)	(0.19)	(0.19)
supergame	0.16**	0.05	−0.12*
	(0.04)	(0.04)	(0.04)
R^2	0.04	0.00	0.02
Num. obs.	10200	10200	10200
N Clusters	10	10	10

Data includes all rounds and only Baseline data for B, Recommendation data for R, and Outsourcing data for O. Results are based on linear regression with clustered standard errors at the matching group level. Significance levels: *** p<0.001; ** p<0.01; * p<0.05.

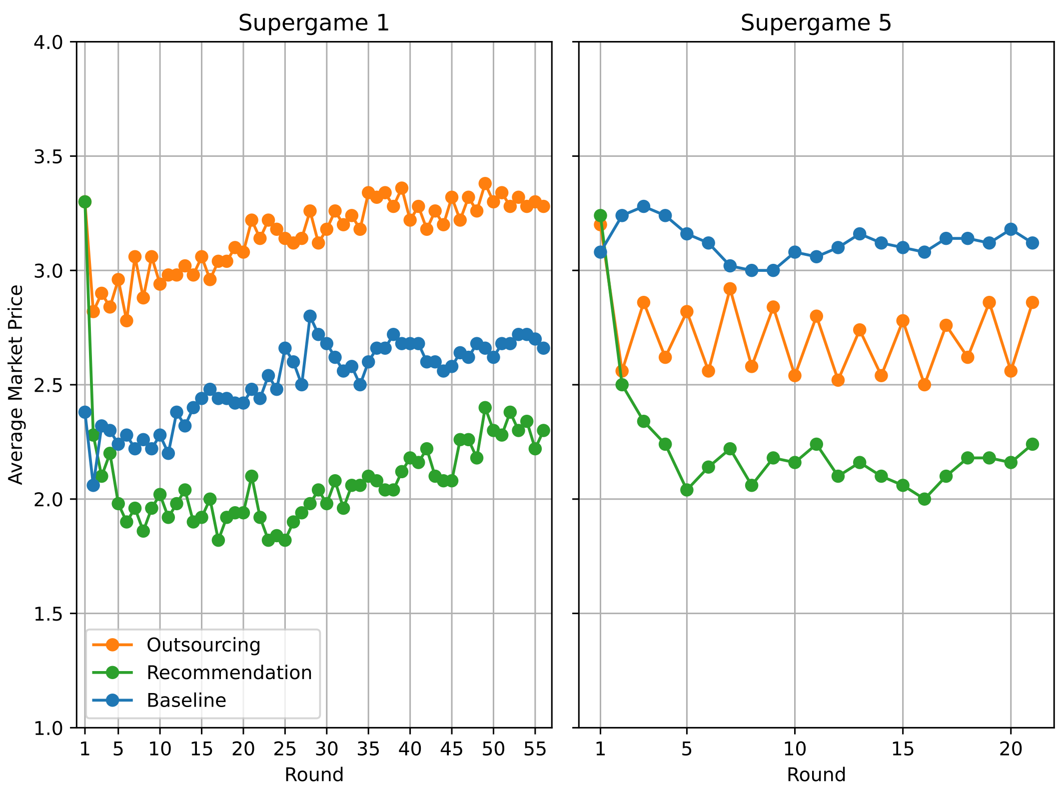

Figure 9: Average Market Prices by Round and Supergame

Table 6: Market Prices by Market Composition and Treatment

	Market Prices		
	(1)	(2)	(3)
AH Market	−0.30	0.87***	0.87***
	(0.55)	(0.10)	(0.10)
AA Market	−0.04	2.32***	2.32***
	(0.58)	(0.12)	(0.11)
Recommendation			0.66
			(0.56)
AH Market x Recommendation			−1.16**
			(0.54)
AA Market x Recommendation			−2.37***
			(0.57)
(Intercept)	2.33***	1.68***	1.68***
	(0.56)	(0.12)	(0.11)
Sub-sample	Rec	Out	Rec&Out
Num. obs.	10200	10200	20400
Num. cluster	20	20	20
R^2	0.01	0.41	0.26

Results are based on linear regression with clustered standard errors at the matching group level. Model (1) is Recommendation only, Model (2) is Outsourcing only, Model (3) is Recommendation and Outsourcing only. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

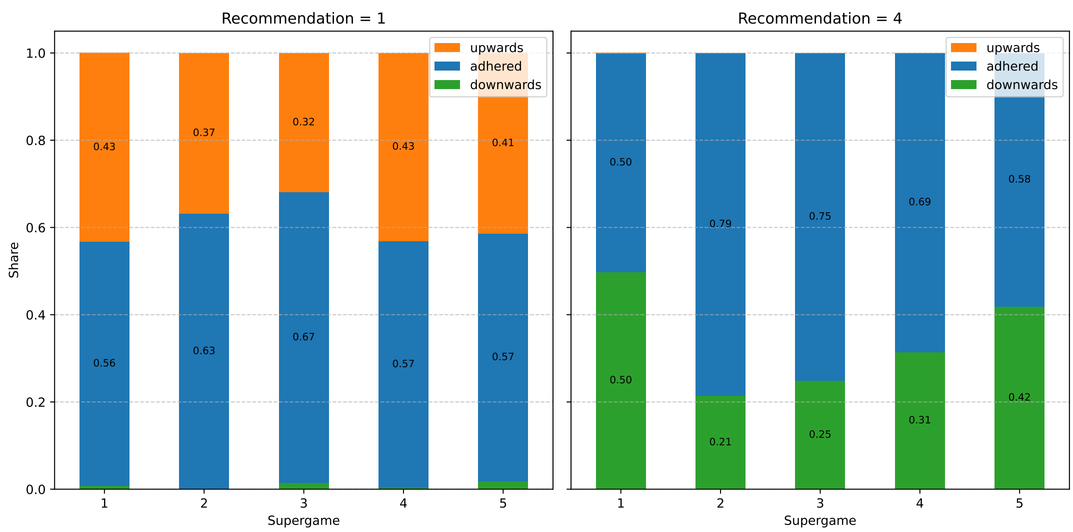

Figure 10: Adherence and Deviations by Type of Algorithmic Recommendations

Table 7: Per-period profits, in Supergames 1 and 5 for Outsourcing and Recommendation treatments.

Outsourcing (SG1)

	Algorithm	No Algorithm
Algorithm	(120.00, 120.00)	(54.74, 95.99)
No Algorithm	(95.99, 54.74)	(49.15, 49.15)

Outsourcing (SG5)

	Algorithm	No Algorithm
Algorithm	(120.00, 120.00)	(72.11, 101.30)
No Algorithm	(101.30, 72.11)	(42.67, 42.67)

Recommendation (SG1)

	Algorithm	No Algorithm
Algorithm	(64.91, 64.91)	(56.17, 56.79)
No Algorithm	(56.79, 56.17)	(—, —)

Recommendation (SG5)

	Algorithm	No Algorithm
Algorithm	(66.18, 66.18)	(68.95, 66.67)
No Algorithm	(66.67, 68.95)	(65.71, 65.71)

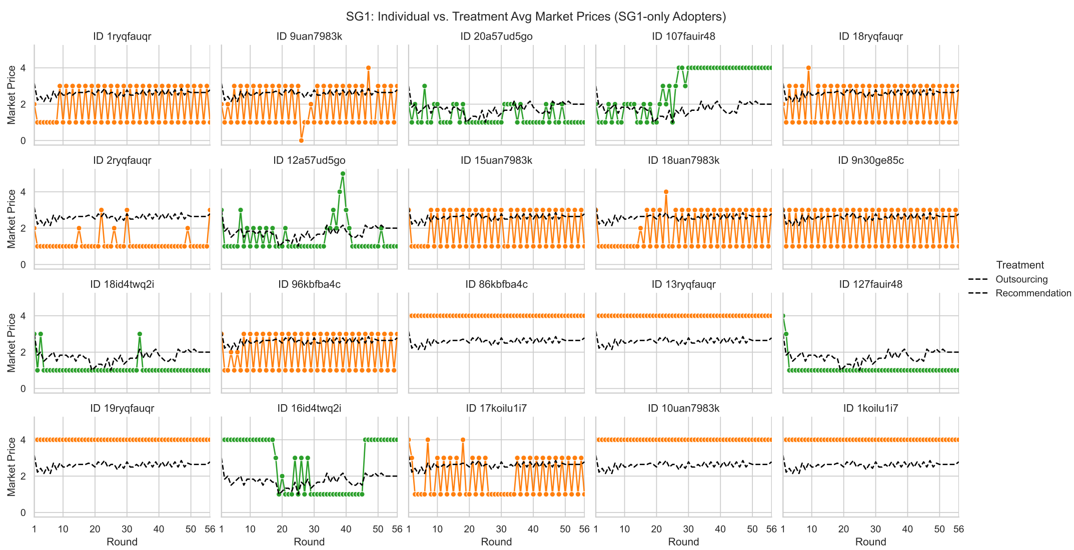

Figure 11: Individual vs. treatment average market prices across round (SG1-only Adopters

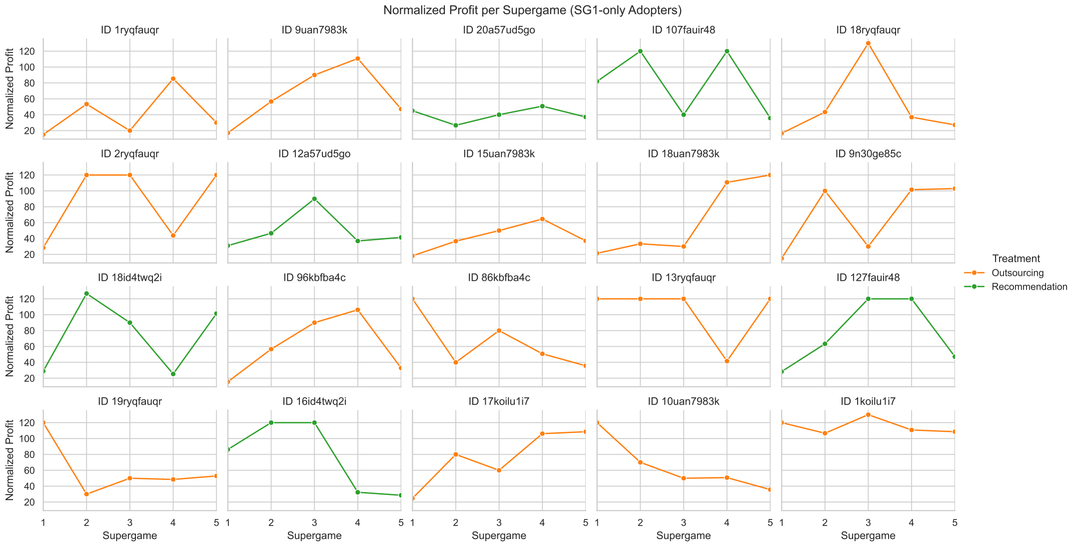

Figure 12: Normalized profit per supergame (SG1-only Adopters)

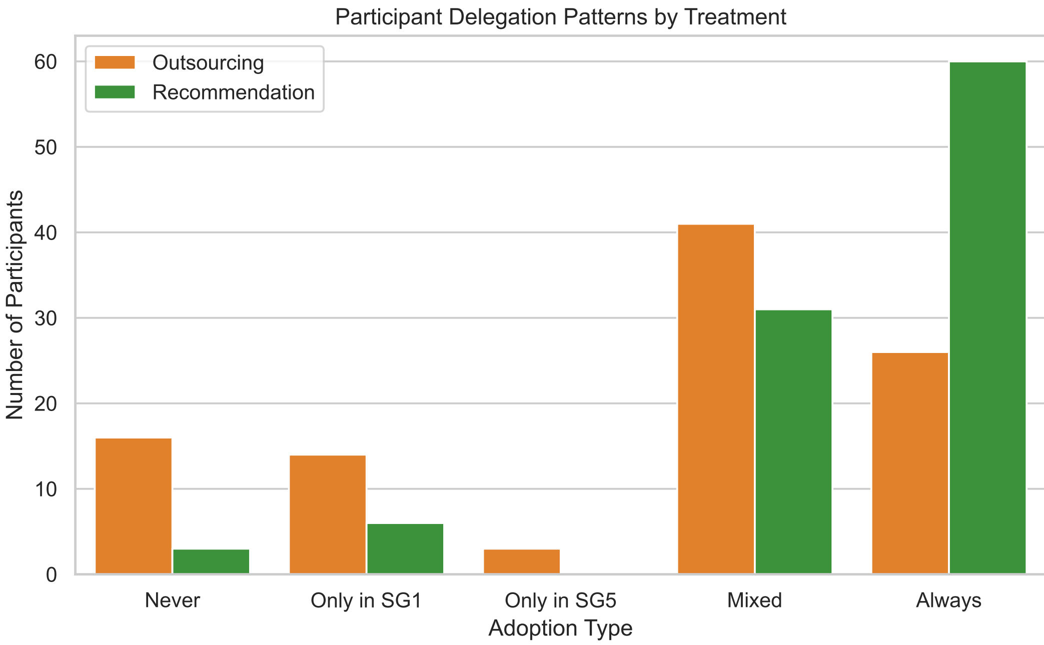

Figure 13: Delegation Pattern by Treatment