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Price-setting algorithms can lead to non-competitive prices, but the law is ill equipped to stop it

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The efficacy of a market system is rooted in competition. In striving to attract customers, firms are led to charge lower prices and deliver better products and services. Nothing more fundamentally undermines this process than collusion, when firms agree not to compete with one another and consequently consumers are harmed by higher prices. Collusion is generally condemned by economists and policymakers and is unlawful in almost all countries. But the increasing delegation of price-setting to algorithms (1) has the potential for opening a backdoor through which firms could collude lawfully (2). Such algorithmic collusion is when artificial intelligence (AI) algorithms learn to adopt collusive pricing rules without human intervention, oversight, or even knowledge. This possibility poses a challenge for policy. To meet this challenge, we propose below a direction for policy change and call for combined efforts of computer scientists, economists, and legal scholars to operationalize the proposed change.

HUMAN COLLUSION

Collusion among humans typically involves three stages (see the table). First, firms' employees with price-setting authority communicate with the intent of agreeing on a collusive rule of conduct. This rule encompasses a higher price and an arrangement to incentivize firms to comply with that higher price rather than undercut it in order to pick up more market share. For example, the CEOs of Christie's and Sotheby's hatched their plans in a limo at Kennedy International Airport, and the U.S. Federal Bureau of Investigation secretly taped the lysine cartel as they conspired in a Maui hotel room. At those meetings, they spoke about charging higher prices and how to enforce them. Second, successful communication results in the mutual adoption of a collusive rule of conduct which commonly takes the form of a collusive pricing rule. A crucial component of this pricing rule is retaliatory pricing: each firm raises its price and maintains that higher price under the threat of a "punishment," such as a temporary price war, should it cheat and deviate from the higher price (3). It is this threat that sustains higher prices than would arise under competition. Third, firms set the higher prices which are the consequence of having adopted those collusive pricing rules.

In order to determine whether firms are colluding, one could look for evidence at any of the three stages. However, evidence related to the last two stages, pricing rules and higher prices, is generally regarded as

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insufficient to achieve the requisite level of confidence in the judicial realm. Economists know how to calculate competitive prices given demand, costs, and other relevant market conditions. But many of these factors are difficult to observe and, when observable, challenging to measure with precision. Consequently, courts do not use the competitive price level as a benchmark to identify collusion. Likewise, it is difficult to assess whether the firms' rules of conduct are collusive because such rules are latent, residing in employees' heads. In practice, we may never observe the retaliatory lower prices from a firm cheating, even though that response is there in the minds of the employees and it is the anticipation of such a response that sustains higher prices. In other words, we might lack the events that produce the data which could identify the collusive pricing rules. Furthermore, even if one could observe what looks like a price war, it would be difficult to rule out innocent explanations (such as a decrease in the firms' costs, or a fall in demand).

Given the latency of collusive pricing rules and the difficulty of determining whether prices are collusive or competitive, antitrust law and enforcement has focused on the first stage: communications. Firms are found to be in violation of the law when communications (perhaps supplemented with other evidence) are sufficient to establish that firms have a "meeting of minds," a "concurrence of wills," or a "conscious commitment" that they will not compete (4). In the U.S., more specifically, there must be evidence that one firm *invited* a competitor to collude and that competitor *accepted* that invitation. The risk of false positives (i.e., wrongly finding firms guilty of collusion) has led courts to avoid basing their judgments on evidence of collusive pricing rules or collusive prices and instead to rely on evidence of communications.

ALGORITHMIC COLLUSION

Though the use of pricing algorithms has a long history - airline companies, for instance, have been using revenue management software for decades - concerns regarding algorithmic collusion have only recently arisen for two reasons. First, pricing algorithms have evolved from programs in which pricing rules are set by programmers, to rely more on AI systems that learn autonomously through active experimentation. After the programmer has set a goal, such as profit maximization, algorithms are capable of autonomously learning rules of conduct that achieve the goal, possibly with no human intervention. The enhanced sophistication of learning algorithms makes it more likely that AI will discover profit-enhancing collusive pricing rules just as they have succeeded in discovering winning strategies in complex board games such as chess and Go (5).

Second, a feature of online markets is that competitors' prices are available to a firm in real time. Such information is essential to the operation of collusive pricing rules. In order for firms to settle on some common higher price, firms' prices must be observed frequently enough because sustaining those higher prices requires the prospect of punishing a firm that deviates from the collusive agreement. The more quickly the punishment is meted out, the less temptation to cheat. Thus, the emergence and persistence of higher prices through collusion is facilitated by rapid detection of competitors' prices, which is now often possible in online markets. For example, the prices of products listed on Amazon may change several times a day but can be monitored with practically no delay.

In light of these developments, concerns regarding the possibility of algorithmic collusion have been raised by government authorities, including the U.S. Federal Trade Commission (FTC) (6) and the European Commission

(7). These concerns are justified as enough evidence has accumulated that autonomous algorithmic collusion is a real risk.

The evidence is both experimental and empirical. On the experimental side, recent research has found the spontaneous emergence of collusion in computer-simulated markets. In these studies, commonly used reinforcement-learning algorithms learned to initiate and sustain collusion in the context of well-accepted economic models of an industry (8-9) (see the figure). Collusion arose with no human intervention other than instructing the AI-enabled learning algorithm to maximize profit (i.e., algorithms were not programmed to collude). While the extent to which prices were higher in such virtual markets varies, prices were almost always substantially above the competitive level

On the empirical side, a recent study (10) has provided possible evidence of algorithmic collusion in Germany's retail gasoline markets. The study finds the delegation of pricing to algorithms was associated with a substantial 20-30 percent increase in the markup of stations' prices over cost. Though the evidence is indirect – because the authors of the study could not directly observe the timing of adoption of the pricing algorithms and thus must infer it from other data – their findings are consistent with that found in computer-simulated markets.

A NEW POLICY APPROACH

Algorithmic collusion is as bad as human collusion. Consumers are harmed by the higher prices, irrespective of how firms arrive at charging these prices. However, should algorithmic collusion emerge in a market and be discovered, society lacks an effective defense to stop it. The reason for this is that algorithmic collusion (which is to be distinguished from instances in which firms' employees might communicate and then collude with the assistance of algorithms, as in a recent case involving poster sellers on Amazon marketplace) does not involve the communications that have been the route to proving unlawful collusion. And even if alternative evidentiary approaches were to arise, there is no liability unless courts are prepared to conclude that AI has a "mind" or a "will" or is "conscious", for otherwise there can be no "meeting of minds" with algorithmic collusion.

As a result, if algorithmic collusion occurs and is discovered by the authorities, currently it is not a violation of antitrust or competition law. Society would then have no recourse and consumers would be forced to continue to suffer the harm from algorithmic collusion's higher prices.

There is an alternative path, which is to target the collusive pricing rules learned by the algorithms that result in higher prices (11). These latent rules of conduct may be uncovered when they have been adopted by algorithms. While a court cannot get inside the head of an employee to determine why prices are what they are, firms' pricing algorithms can be audited and tested in controlled environments. One can then simulate all sorts of possible deviations from existing prices and observe the algorithms' reaction in the absence of any confounding factor. In principle, the latent pricing rules can thus be identified precisely.

This approach was successfully used by researchers in (8) to verify that the pricing algorithms have indeed learned the collusive property of reward (keeping prices high unless a price cut occurs) and punishment (through retaliatory price wars should a price cut occur). To show this, researchers momentarily overrode the pricing algorithm of one firm, forcing it to set a lower price. As soon as the algorithms regained control of the pricing, they engaged in a temporary price war, where lower prices were charged but then gradually returned to the collusive level. Having learned that undercutting the other firm's price brings forth a price war (with the associated lower profits), the algorithms evolved to maintain high prices (see the figure).

It may seem paradoxical that collusion is identified by the low retaliatory prices, which could be close to the competitive level, rather than by the high prices that are the ultimate concern for policy. But there are two important differences between retaliatory price wars and healthy competition. First, in the absence of the low-price perturbation, the price war remains hypothetical in that it is a threat that is not executed. Second, the price war in the figure is only temporary: instead of permanently reverting to the competitive price level, the algorithms gradually return to the pre-shock prices. This is evidence that the price war is there to support high prices, not to produce low prices.

Focusing on the collusive pricing rules is the key to identifying, preventing, and prosecuting algorithmic collusion (see table). Policy cannot target the higher prices directly and (unlike with human collusion) it cannot target communications either as they may not be present. But the retaliatory pricing rules may now be observable, as firms' pricing algorithms can be audited and tested. We therefore propose that antitrust policy shift its focus from communications (with humans) to rules of conduct (with algorithms).

Making the proposed change operational involves a broad research program that requires the combined efforts of economists, computer scientists, and legal scholars. One strand of this program is a three-step experimental procedure. The first step creates collusion in the lab for descriptively realistic models of markets. As the competitive price would be known by the experimenter, collusion is identified by high prices. Having identified an episode of collusion, the second step is to perform a post-hoc auditing exercise to uncover the properties of the collusive pricing rules producing those high prices.

While some progress has been made on the identification of collusive rules of conduct adopted by algorithms, much more work needs to be done. Economics provides several properties to watch out for. Of course, there is the retaliatory price war discussed above, which is what existing research has focused on (8-9). Another property is price matching, whereby firms' prices move in sync: one firm changing its price and the other firm subsequently matching that change. Price matching has been documented for human collusion in various markets but we do not yet know whether algorithms are capable of learning it. A third property is the asymmetry of price responses. When firms collude, they typically respond to a competitor's price cut more strongly – as part of a punishment – than to a price increase. No such asymmetry is to be expected when firms compete.

The aforementioned properties are based on economic theory and studies of human collusion. Learning algorithms may devise rules of conduct that neither economists nor managers have imagined (just as learning algorithms have done, for instance, in chess). To investigate this possibility, computer scientists might develop algorithms that explain their own behavior thereby making the collusive properties more apparent. One way of doing so is to add to the reinforcement-learning module that maximizes profits a second module, which maps the state representation of the former onto a verbal explanation of its strategy (12).

Having uncovered collusive pricing rules, the third step is to experiment with constraining the learning algorithm in order to prevent it from evolving to collusion. Computer scientists are particularly valuable here given they are involved in similar tasks such as trying to constrain algorithms so that, for instance, they do not exhibit racial and gender bias (13).

Once having developed the capacity to audit pricing algorithms for collusive properties and constrain learning algorithms so they do not adopt collusive pricing rules, legal scholars are called upon to use that knowledge for purposes of prosecution and prevention. One route is to make certain pricing algorithms unlawful, perhaps under Section 5 of the FTC Act which prohibits unfair methods of competition. In the area of securities law, the 2017 case *U.S. v. Michael Coscia* made illegal the use of certain programmed trading rules and thus provides a legal precedent for prohibiting algorithms. Another path is to make firms legally responsible for the pricing rules that their learning algorithms adopt (14). Firms may then be incentivized to prevent collusion by routinely monitoring the output of their learning algorithms.

These are some of the avenues that can be pursued for preventing and shutting down algorithmic collusion. There are several obstacles down the road, from making a collusive property test operational, to the lack of transparency and interpretability of algorithms, to courts willingness and ability to incorporate technical material of this nature. In addition, there is the challenge of addressing algorithmic collusion without giving up the efficiency gains from pricing algorithms such as the quicker response to changing market conditions. As authorities prepare to take action (15), it is vital that computer scientists, economists, and legal scholars work together to protect consumers from the potential harm of higher prices.

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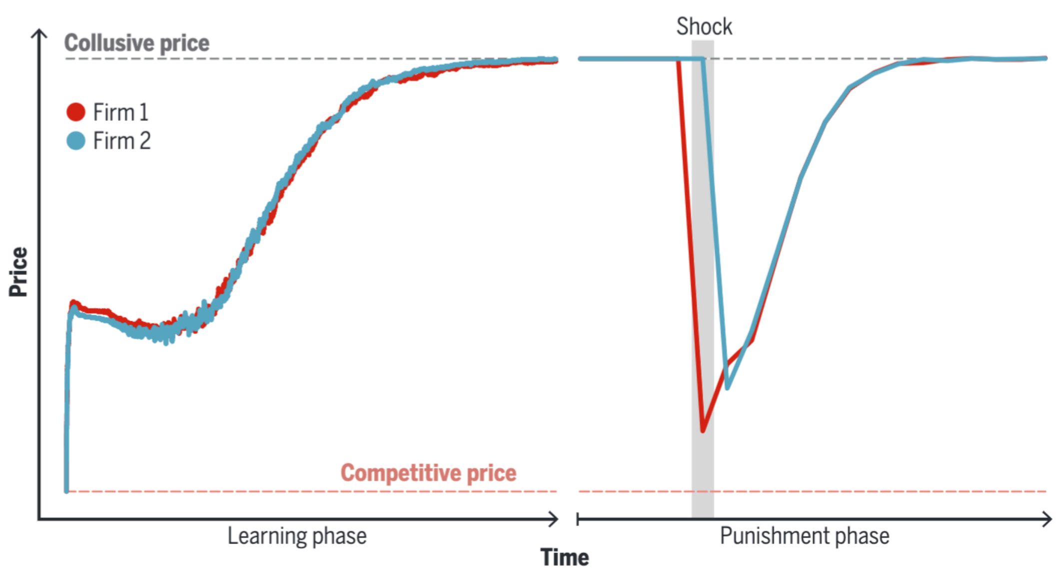
Table. The process that produces higher prices.

	Communications	Collusive pricing rules	Higher prices
Humans	Present, discoverable	Latent, not discoverable	Observable, difficult to evaluate
Algorithms	Not present	Latent, discoverable	Observable, difficult to evaluate

Figure. Collusive pricing rules uncovered.



After the two algorithms have found their way to collusive prices (the learning phase on the left-hand side), an attempt to cheat so as to gain market share is simulated by exogenously forcing Firm 1's algorithm to cut its price. From the "shock" period onwards, the algorithm regains control of the pricing. Firm 1's deviation is punished by the other algorithm, so firms enter into a price war that lasts for several periods and then gradually ends as the algorithms return to pricing at a collusive level. (For better graphical representation, the time scale on the right-hand side of the figure is much larger than on the right-hand side.) Adapted from (8).