What Do We Know About Algorithmic Collusion Now? New Insights from the Latest Academic Research

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Introduction

Algorithmic collusion has captured the attention of the global antitrust community for the past several years. Deng (2020) provided a comprehensive survey of the pertinent literature in economics and computer science and a critical discussion. Over the past three years, new insights have emerged from academic research. These new insights have not only deepened our understanding of the intricate relationship between algorithms and competition but also begun challenging some previous findings once considered compelling evidence supporting the plausibility of autonomous algorithmic tacit collusion. In this article, I discuss these new insights, with a focus on four topics: (1) the nuanced ways algorithms affect prices, (2) the crucial role of algorithmic design, (3) the consequences of third-party pricing algorithms, and (4) some considerations when assessing algorithmic impact in litigation.

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3 While I focus on algorithmic collusion in this article, the implications of AI algorithms on other aspects of competition have been explored as well. For a discussion about the antitrust implications of algorithms on unilateral conduct such as exclusion and foreclosure, see Thomas K. Cheng & Julian Nowag, Algorithmic Predation and Exclusion, 25 J. BUS. L. 41 (2023). For the implications of pricing algorithms on horizontal mergers, See, e.g., Deng and Hernandez (2023) and Coutts (2023). Ai Deng & Cristián Hernández, Algorithmic Pricing in Horizontal Merger Review: An Initial Assessment, ANTITRUST MAG., Apr. 2022. Michael David Coutts, Mergers, Acquisitions and Merger Control in an Algorithmic Pricing World, 19(1) J. OF COMP LAW & ECON. (2023). Deng (2020), supra
What Is Algorithmic Collusion?

What exactly is collusion? While human collusion is often defined as “a meeting of the minds,” either explicitly through communications or tacitly through conscious parallelism, the definition of collusion when it comes to pricing algorithms may not appear to be as obvious. However, one thing most scholars and practitioners would agree on is that a supracompetitive price in and of itself is not synonymous with (tacit) collusion.

Harrington (2022) provided a useful definition of collusion. He emphasizes that “collusion is when firms use strategies that embody a reward-punishment scheme that rewards a firm for abiding by the supracompetitive outcome and punishes it for departing from it,” so “a ‘collusive strategy’ refers to a reward-punishment scheme.” On the basis of this definition, when inferring whether algorithmic collusion exists, analyzing the algorithmic pricing behavior, rather than looking at just the algorithmic prices, is important.

Pricing Algorithms Affect Prices in Multiple Ways

Indeed, recent economic literature has revealed complex and yet subtle ways in which pricing algorithms, sometimes with human intervention, impact market prices. One key takeaway is that not all mechanisms can be said to be collusive.

Hansen et al. (2021) showed that in an oligopolistic market, if demand is relatively deterministic and firms all behave as if they are monopolists (i.e., ignore the impact of competitors’ prices on their own profit) and run price experiments to determine the best price to charge using certain algorithms, the resulting prices could be supracompetitive. Cooper et al. (2015) similarly showed that ignoring competition may lead to supracompetitive prices. Note that these studies do not involve algorithmic behavior resembling reward and punishment.

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note 2, also discussed the computer science literature on cooperative AI. That literature continues to grow but is outside of the scope of this article.

4 Whether an algorithm is necessarily mindless is itself an interesting philosophical question. Some have argued that an algorithm may, in fact, have intentions. See, e.g., Hal Ashton, Definitions of Intent Suitable for Algorithms, A.I. & L. (2022), https://doi.org/10.1007/s10506-022-09322-x.

5 While this position is hardly controversial, there is an unfortunate tendency to label any conduct collusion simply because the use of algorithms leads to higher prices.

6 Joseph Harrington, Developing Competition Law for Collusion by Autonomous Artificial Agent, 14 J. COMPETITION L. & ECON. 331 (2019).

7 See Karsten T. Hansen et al., Algorithmic Collusion: Supra-competitive Prices via Independent Algorithms, 40 MKTG. SCI. 1, 11–12 (2021), https://doi.org/10.1287/mksc.2020.1276. The main intuition behind this result is that by behaving as monopolies in an oligopolistic environment, firms overestimate their own price sensitivity, resulting in higher prices. The researchers further showed that in their framework, demand uncertainty (i.e., signal-to-noise ratio) is one of the key drivers of their finding: if demand is sufficiently random, then the resulting prices may be close to the competitive level.

8 William L. Cooper et al., Learning and Pricing with Models That Do Not Explicitly Incorporate Competition, 63 OPERATIONS RSCH. 86 (2015).
Brown and MacKay (2022) showed that if firms can choose their pricing frequency, each firm may have a unilateral profit incentive to choose a frequency different from the frequencies of their competitors. This could again lead to higher prices, even when they “eliminate collusive strategies that rely on cooperate-or-punish schemed.” The basic intuition is that “a superior-technology firm commits to ‘beat’ (best respond to) whatever price is offered by its rivals . . . . The rivals take this into account, softening price competition.” Note that this result holds under their assumptions regardless of whether the price is set by algorithms or humans. However, the authors argue that the use of pricing algorithms makes firms’ commitment to respond at given frequencies credible. The findings led the researchers to conclude that “algorithms fundamentally change the pricing game, providing a means to increase prices without resorting to collusive behavior.” In other words, by increasing competitive prices and profits, algorithms could actually reduce the likelihood of collusion because they may “make punishment less severe in a collusive scheme.” This study thereby made a strong case for not equating supracompetitive prices to algorithmic collusion.

**Autonomous Algorithmic Collusion?**

Calvano et al. (2022) is an often-cited academic study once believed to have provided the most convincing evidence to date for autonomous algorithmic collusion without human instruction or explicit communications. In a nutshell, using computer simulations, the authors constructed a pricing algorithm using a standard reinforcement learning (RL) method known as Q-learning and showed that when it simply unilaterally tries to maximize profit, the algorithm learns to set supracompetitive prices. The most intriguing finding, however, is that their algorithm appears to have learned to adopt a reward-punishment scheme: when the researchers initiated a price cut for one of the competitors, the algorithm of the other competitor immediately, without human instruction, set an even lower price, as if it were punishing the deviation. They also found that after the initial episodes of “cheating” and “punishment,” both algorithms appeared to gradually raise their prices back to the supracompetitive level. I have previously discussed this article in detail and highlighted several limitations of the study pertaining to its implications for real-world pricing algorithms. Recent studies in economics and operational research have begun exploring these limitations more rigorously.

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10 *Id.* at 111.

11 The idea that using algorithms can be seen as a commitment device has also been explored by other studies. For example, the “commitment-enhancing features of algorithms” are an important consideration in Leisten’s (2022) study of algorithmic pricing with human intervention. Matthew Leisten, *Algorithmic Competition, with Humans* (Dec. 17, 2022), [https://www.dropbox.com/s/pk83ocy9in8is8c/Algorithmic_Competition__with_Humans.pdf?dl=0](https://www.dropbox.com/s/pk83ocy9in8is8c/Algorithmic_Competition__with_Humans.pdf?dl=0).

12 *Id.* at 111.

13 *Id.* at 112.


One such study was carried out by Andrea Epivent and Xavier Lambin (2023). They focused on Calvano et al.’s (2022) experimental finding that their pricing algorithms learned to punish competitors who initiated a price cut. After observing that Calvano et al.’s pricing algorithms set a price still lower than the monopoly price, Epivent and Lambin investigated the algorithm’s responses to an invitation to raise a price. They reasoned that if the algorithms were truly collusive, “such price deviations should benefit the other cartelist and may even invite reciprocity.” However, they observed that price increases “are followed by the same price war as those that follow a price cut.” In the researchers’ words, this observation “raises doubt about whether algorithms truly collude or simply fail to learn to compete.” They concluded that their findings show that “the apparent reward-punishment schemes may not be fully rational and may stem from the imperfect of the learning process, rather than algorithmic sophistication” and that “collusion is not the only possible explanation on apparent punishments or supracompetitive profits of AIA (Artificial Intelligence Algorithm).”

In another study, Arnoud V. den Boer, Janus M. Meylahn, and Maarten Pieter Schinkel (2022) took a comprehensive look at other aspects of Calvano et al.’s findings. They investigated and consequently formalized several limitations of Calvano et al. that I discussed earlier. For example, the authors investigated the reasons “training” the pricing algorithm takes a significant amount of time and discussed why Calvano et al.’s conclusion that their algorithm learns to collude is incorrect. Additionally, Arnoud et al. argued that if a competitor adopts Calvano et al.’s algorithm, it can be exploited by other algorithms that would disadvantage the adopter. This therefore casts doubt on the belief that rational firms would unilaterally adopt their algorithm or otherwise continue to use the algorithm after adoption. See an earlier discussion along these lines in Deng (2020). Arnoud et al. ultimately concluded that

the simulations presented by Calvano et al. do not give sufficient evidence for the claim that these types of Q-learning algorithms systematically learn collusive strategies. . . . The same is true for the claim that the supracompetitive prices generated by the algorithms are often supported by collusive equilibria. That the algorithms would generate sizable extra-profit is true for some price-sets and false for other price-sets and is determined by factors unrelated to collusion. . . . We conclude that warnings that algorithmic collusion via these types of Q-learning algorithms . . . should ‘ring an alarm bell with competition authorities, are premature.’

Algorithmic Design Matters

Asker, Fershtman, and Pakes (2022) derived additional insights by opening the algorithmic “black box.” They showed that the pricing algorithm of Calvano et al. can learn to set supracompetitive prices even when it does not possess the features of a collusive strategy. They also showed that when the algorithm takes into account basic economic principles such as downward sloping demand so it understands that higher prices tend to lower quantity demanded, all else being equal (they call it “synchronized learning”), the price levels can be significantly lower than those set by an algorithm that does not recognize such economic principles. The key takeaway is that the design of algorithms can have a significant impact on

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17 Deng, Algorithmic Collusion, supra note 2.
algorithmic prices. This finding led the researchers to ultimately conclude that “the results in this paper point toward procompetitive implementations being those that are informed by an understanding of the wider economic environment and that incorporate counterfactual alternatives to the play actually engaged in when learning.”

Banchio and Skrzypacz (2022) studied the impact of the Q-learning algorithm in an auction context and reached a similar conclusion.19 In a simple, symmetric two-bidder case, they compared the first- and second-price auctions and found that the auction format makes a significant difference. While the algorithm in the second-price auction learns to bid competitively, it learns to bid much lower in the first-price auction. Banchio and Skrzypacz also found that if the algorithm is given information about the winning bid after the auction, with synchronized learning, it learns to bid competitively even in the first-price-auction setting. For antitrust practitioners, the message is clear: algorithmic conduct can vary, to a large degree, by algorithmic design as well as by information available to the algorithm.20

Further demonstrating the importance of algorithmic design in an algorithm’s capability to learn to collude, Meylahn and den Boer (2022) developed a pricing algorithm that appears to achieve the best of both worlds in a duopoly: “when the algorithm is used by both sellers in a duopoly, it learns to collude when this is profitable for both firms”; otherwise, “it learns to price competitively when playing against a strategy from a reasonable class of strategies.”21 Not surprisingly, their algorithm is the result of an elaborate design, or as the authors put it, “is explicitly designed to collude.”22 Loots and den Boer (2022) extended Meylahn and de Boer (2022) by developing what they called the “collude-or-compete” algorithm.23 Like the algorithm of Meylahn and den Boer (2022), their algorithm is designed to be able to switch between two modules. One module is designed to collude if used by both firms, and the other is designed to be competitive when a competitor uses other pricing strategies.24 For their algorithm to reach a collusive outcome, it is important that firms know the private demand information of the competitor and the collusive module is activated at the same time. They showed that both conditions are “guaranteed” by the construction of their algorithm. The intuition behind the first result is easy to understand. When both firms use their algorithm, AI can reverse engineer the private demand information based on (public) price information. In other words, the algorithm knows how the copy of itself would price under various demand conditions, which allows it to figure out the demand conditions given the observed prices through reverse engineering.25

20 The fact that design matters is not surprising; see ample evidence of this in Deng, Algorithmic Collusion, supra note 2. These studies are among the first to demonstrate it in the context of pricing algorithms.
22 Id. at 2580.
23 Thomas Loots & Arnoud V. den Boer, Data-driven Collusion, and Competition in a Pricing Duopoly with Multinomial Logit Demand, 32 PROD. & OPERATIONS MGMT. 1169 (2023).
24 The authors also provided several notions of collusion. For this discussion, the exact definition of “collusion” does not matter.
25 It is worth noting that none of these results are assumption-free. As one example, the researchers assumed that “the time required to observe the competitor’s price and potentially adapt one’s price in response to this observation” is sufficiently small. Id. at 1180.
Another study published in 2023 introduced the concept of adversarial collusion. This is the situation where one firm’s algorithm manipulates competitors’ algorithms into collusion. Such an adversarial algorithm can (1) learn competitors’ algorithms and then (2) derive a strategy to either artificially increase its profit at the expense of the competitors or increase the profits of all firms. The researchers demonstrated that in a stylized framework, such an algorithm can indeed be designed. They concluded that this could lead to “a collusive outcome with symmetric and supracompetitive profits, sustainable in the long run.”

While these researchers all suggested that deploying algorithms like those they developed may not violate antitrust laws because they involve no explicit communication or coordination between either humans or AIs, private plaintiffs and antitrust agencies will undoubtedly highlight the fact that firms knowingly deploy a pricing algorithm explicitly designed to collude. In addition, as Deng (2020) pointed out, the elaborate design process of these algorithms necessarily leaves a paper trail that is discoverable in an investigation or in litigation.

### Third-party Pricing Algorithms

With the emergence and expected increasing adoption of third-party pricing algorithms, Harrington (2022) is a highly pertinent study that examined the effect of third-party pricing algorithms on competition. He recognized that the profit incentive of a firm making profit from the sale of the pricing algorithm can be different from that of a firm profiting from the sale of the product the pricing algorithm is to price. He emphasizes that, intuitively,

> a critical distinction between a pricing algorithm designed by a third-party developer who intends to sell it and a firm who intends to use it is that the third party will take account of the possibility that the algorithm might compete against itself; that is, competitors might adopt the pricing algorithm. This could lead the third party to make the pricing algorithm less competitive in order to enhance the algorithm’s performance and thus the demand for it.

Interestingly, Harrington did not find that outsourcing the pricing algorithm would lead to higher average prices. The basic intuition is that “if the pricing algorithm sets higher prices, it will also make it more attractive for a firm not to adopt because it can profitably undercut the prices set by rival firms who did adopt.” [emphasis original]. He found that “what the third party does instead is make price more sensitive to demand variation, thereby generating more profit when and where demand is strong,” and “by making price more sensitive to demand variation, the third party improves the profit from joint adoption without making it more attractive not to adopt.” Harrington further argued that while the average price is not higher, outsourcing still harms consumers because of increased price variability. However, it is important to note that such an algorithm can, for the same reason, offer lower prices to consumers during

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26 Luc Rocher et al., *Adversarial Competition and Collusion in Algorithmic Markets*, 5 NATURE MACH. INTEL. 1 (2023).
29 Id. At 6898.
30 Id. At 6890.
the period of low demand. Of course, in antitrust litigation, consumer harm, or benefit for that matter, if any, can be assessed only in comparison to an appropriate benchmark, a topic we return to in the next section.

As Harrington (2022) was one of the first studies of third-party pricing algorithms, many unanswered questions remain. Several practical realities are important to explore.\(^{31}\) First, we need to recognize that there are at least two types of third-party providers. Some providers may simply develop and sell their algorithm to their customers as a piece of software. They provide necessary technical support, but customers have the responsibility to “run” the algorithms and can easily overwrite them as they wish. Some other providers may be best characterized as providing an outsourcing service in which the pricing decision is completely delegated to the third party. These two scenarios may differ from each other regarding the information input into the pricing algorithm and the feasibility and ease of overwriting. Second, competition among multiple third-party developers presents another interesting situation.\(^{32}\) Developers may compete in two dimensions: (1) the pricing of their algorithmic services and (2) the design features of their algorithms. Regarding the former, some developers may charge a fixed monthly fee, while others charge a percentage of transaction amount.\(^{33}\) Different pricing structures imply different economic incentives on the part of the developers.\(^{34}\) Regarding the latter, except for simple repricing algorithms such as those used by small third-party sellers on various online shopping platforms, sophisticated developers often allow substantial customization of a client’s and hence the algorithm’s objective. These objectives may include increasing market share, reducing inventory, increasing transaction volume, or increasing revenue, among others.\(^{35}\) In this scenario, using the same third-party algorithm does not mean using an identical pricing algorithm.

Finding the Right Benchmark

Often buried in the academic literature is the question of what an appropriate benchmark is for assessing algorithmic impact. Most, if not all, academic studies compare algorithmic prices to those that would prevail under the most ideal competitive conditions. This is understandable because such a comparison often yields a sharp prediction. In litigation, however, impact and damages are most often assessed based

\(^{31}\) It is also worth noting that in order to derive these new insights, Harrington did not allow the algorithm to condition on how many firms adopted because otherwise “the third party could design the algorithm to price at the monopoly level” only when all firms adopted, and otherwise price competitively. The algorithm also cannot condition on competitor prices. Id. at 6897, 6899.

\(^{32}\) See also Id. at 6898 (“A critical extension is to allow for multiple third-party developers who compete in designing and selling their pricing algorithms.”)

\(^{33}\) For example, multiple companies provide pricing services for short-term rental units. The company Beyond charges a percentage of all bookings, while another company, PriceLabs, charges by the number of listings. See Pricing Packages for Businesses at Any Stage, BEYOND, https://www.beyondpricing.com/plans (last visited July 7, 2023); Simple, Affordable Pricing, PRICELABS, https://hello.pricelabs.co/plans/ (last visited July 7, 2023).

\(^{34}\) Additional discussion on this important point can be found in Id at 6897 (“the fee was not allowed to be tied to an adopting firm’s profit. Without that restriction, the third-party could claim a share of firms’ profit and thus be incentivized to have the pricing algorithm charge the monopoly price so as to maximize industry profit.”)

\(^{35}\) For example, Competera, a pricing service provider, emphasizes the importance of aligning pricing strategy with business objectives. Original Prices Your Customers Trust, COMPETERA, https://competera.net/ (last visited July 7, 2023).
on a comparison between the actual world and the counterfactual world where the alleged anticompetitive conduct did not occur.

In characterizing the proper counterfactual in a litigation context, several important factors should be considered. I discuss two in this section. First, the time periods before and sometimes after the alleged conduct are often used as a benchmark. Following this practice, it may be tempting to use the time periods before the adoption of the algorithm as the benchmark. The appropriateness of this practice, however, depends on, among other things, whether the algorithm learns online or offline. Simply put, an online-learning algorithm is trained dynamically using market responses to algorithmic decisions over a period of time, all based on real-time data. Many algorithms, especially those known as “reinforcement learning” algorithms, are characterized by their learning through trial and error. As a result, if the algorithms in question learned online, it is likely inappropriate to include the training period, which, by definition, is post adoption, as a part of the benchmark to assess the ultimate impact. While this is an important consideration, it does not present an insurmountable challenge. Identifying the end of the training phase should be technically possible in many cases. Offline learning, also known as “batch” learning, is typically static and based on historical data. Because the training takes place offline and the algorithm is deployed only after it has finished the training, the issue raised above does not arise.

Another question pertains to the situation where the algorithm of interest also has a procompetitive module. For example, suppose the algorithm reduces the marginal cost of production. An important question is whether the counterfactual world should allow the firms to enjoy such efficiency gains. If the answer is yes, then defining the counterfactual world as one without the algorithm at all would not be appropriate. A practical challenge may arise, however, when there is no clean separation between various algorithmic modules. A general prescription does not exist, and the solution will necessarily be case specific.

Conclusions

Recent research in economics has shed much new light on pricing algorithms and collusion. It has revealed additional nuances and complexity in the ways pricing algorithms can affect prices. Some studies have shown that algorithms may increase prices without tacit coordination or a reward-punishment scheme. Others have identified potential issues with the use of the simple profit-maximizing algorithm that many, just a couple of years ago, believed to be capable of learning to autonomously collude.

Recently, some have proposed regulating pricing algorithms, including the possibility of preventing an algorithm from using competitor prices as an input and limiting how frequently a pricing algorithm could update prices. From a practical standpoint, these proposals appear to be premature at this moment. Not

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36 It is important to note that while the training phase may not be appropriate for the purpose of assessing the ultimate impact, it can be an important input in understanding how the algorithm works. For more discussion on the topic in the context of algorithmic compliance, see Deng (2020), supra note 2.

only are such restrictions difficult to make precise (consider the question of how frequent is too frequent), but compliance with them would be difficult to monitor (consider the situation where human managers overwrite algorithmic prices based on prohibited inputs with little written record or paper trail). More fundamentally, we have seen evidence that algorithmic design and the data input can make a meaningful difference in algorithmic pricing behavior. Given the many procompetitive benefits of algorithmic pricing, any blanketed restrictions on either the design or the input should be carefully vetted so we do not unintentionally rule out competitive algorithms. Indeed, there is still much that we do not know. Of course, the literature has also shown that it is possible to explicitly design collusive algorithms. The design process of such algorithms, however, can be uncovered ex post, making clear the intent of the algorithm developers.

Even though we are still grappling with the profound implications of AI on competition, from a compliance and consumer protection perspective, it is prudent for companies adopting a pricing algorithm to understand what information is being provided to the pricing algorithm, what the pricing algorithm does, and in what ways it increases their profitability or helps achieve other business objectives.

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38 One such unknown relates to the specific algorithms. Many recent studies, motivated by Calvano et al. (2020), considered the relatively simple Q learning algorithm. Banchio and Skrzypacz (2022) acknowledged that “more sophisticated algorithms are of interest,” such as those that “depend on recent history, like who won the last auction.” But they are “much harder to analyze.”