New pricing technology has arrived on the scene in the last few years, namely pricing algorithms. As the use of pricing algorithms increase, antitrust agencies and lawyers will be required to address them in litigation, as part of client compliance programs, and determining what economic impact they may achieve. Antitrust lawyers will need to investigate the use of pricing algorithms, and this newsletter grapples with what tools may be used in that pursuit. Can the traditional legal and economic framework of antitrust be applied to new
technical capabilities that are being embraced by companies to establish prices via algorithm? We hope that the articles within this newsletter help begin the dialogue about how to answer that question.

Sincerely yours,

Megan Jones
Partner
Hausfeld LLP

A LITIGATOR’S APPROACH TO PRICING ALGORITHMS CASES: WHAT WILL WE NEED TO KNOW?

Pricing algorithms are not new. Pricing algorithms at the heart of antitrust cases are: but for how long? If you recently bought anything on Amazon, “an algorithm rather than a human probably set the price of the service or item you bought.”

Third-party firms have sprung up to sell pricing algorithms to retailers or even directly take on the role of pricing using computer models on behalf of their clients. As recently noted, Silicon Valley companies are routinely hiring Ph.D.’s in economics to harness the huge swaths of data that companies are collecting. It may not be long before pricing algorithms are the centerpiece of an antitrust cartel case. In that case, what used to be common areas of inquiry in antitrust cases (volume discounts, long term contracts, and price lists) may soon be replaced by code, artificial intelligence and algorithm design. Thus, in antitrust parlance, the primacy of the deposition of the Vice President of Sales may soon be replaced by the computer scientist(s) and economists who created the pricing code of the algorithm. This article is forward looking, and attempts to outline what may be the potential issues for discovery in a pricing algorithm case.

1. Who (Or What) Actually Colluded?

What happens when a pricing algorithm learns to collude with an independent pricing algorithm? For example,

Researchers at the University of Bologna in Italy created two simple reinforcement-learning-based pricing algorithms and set them loose in a controlled environment. They discovered that the two completely autonomous algorithms learned to respond to one another’s behavior and quickly pulled the price of goods beyond where it would have been had either operated alone.

“What is most worrying is that the algorithms leave no trace of concerted action,” the researchers wrote. “They learn to collude purely by trial and error, with no prior knowledge of the environment in which they operate, without communicating with one another, and without being specifically designed or instructed to collude.” This risks driving up the price of goods and ultimately harming consumers.

In the above scenario, is there a conspiracy? That example, and others that will follow, make it clear that the contours of a conspiracy may be buried in code. Whether there is a conspiracy may turn on whether the algorithm is merely administering an existing agreement to collude (express agreement), or whether the algorithm results from two or more firms using algorithms to make unilateral pricing decisions that involve interdependent conduct (tacit agreement). Areas of discovery to deduce what actually happened could include:

(a) Typical areas of collusion (that the algorithm merely memorialized);
(b) The basis of the algorithm and its inputs;
(c) Whether the algorithm was dependent on rival’s pricing;
(d) Whether there was an incentive to deviate from the algorithm to undercut rivals;
(e) Whether the algorithm was designed or instructed to collude;
(f) Whether the algorithm reacted in a predictable way in order to signal the rivals’ future actions;
(g) Who at the company approved of the algorithm and his or her underlying reasoning for its creation;
(h) Whether the rivals are using the same algorithm, and if so, how did that come to be;
(i) Whether the algorithm was designed to detect “cheating” by rivals;
(j) Whether a third party sold the same algorithm to rivals, and if so, what promises were made;
(k) What was the intended outcome of the algorithm; and
(l) Whether the algorithm was designed to use rival actions.

Instead of calling the salesperson to the witness stand, antitrust lawyers in the future may be cross-examining coders about who approved specific design elements.

2. Did the Algorithm Actually Harm Consumers?

The use of pricing algorithms could potentially benefit firms and/or consumers in many situations. They could “reduce transaction costs for firms, reduce frictions in markets, and give consumers greater information on which to base their decisions.” It may also “make explicitly collusive agreements more stable. For example, algorithms may make it easier to detect and respond to deviations, and reduce the chance of errors or accidental deviations from the collusive agreement.” Lawyers and their economists in the future may need to analyze what the actual impact of the algorithm is, and what it was designed to accomplish.

3. What Type of Algorithm Is It?

Algorithms can address a variety of tasks, and span the spectrum of complexity. Lawyers will need to delve into what actions result from simple coding, and what actions result from machine learning (algorithms that are left to decide what data it considers most relevant to meeting its objective). This could result in the proverbial “black box” that lawyers and the courts will have to untangle in order to determine culpability. Specifically, employees who instruct the algorithm may not even know what variables it ultimately used. Lawyers will need to determine what type of algorithm it is, and what it was designed to accomplish.

What is clear is that as the prevalence of pricing algorithms increases, the types of discovery that antitrust lawyers will need to marshal will differ markedly from the past.

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1 Megan Jones is a partner at Hausfeld LLP in San Francisco.
4 See https://www.technologyreview.com/the-download/612947/pricing-algorithms-can-learn-to-collude-with-each-other-to-raise-prices/.
6 Id. at ¶ 7.
TACIT ALGORITHMIC COLLUSION AND ANTITRUST ENFORCEMENT: IS THERE A REASONABLE ENFORCEMENT FRAMEWORK?

Jon M. Woodruff, Associate, Stinson Leonard Street LLP

In his recent article, What Do We Know About Algorithmic Tacit Collusion?, Ai Deng summarizes recent developments within the artificial intelligence (“AI”) and economics literature broadly indicating that while the development of algorithms capable of colluding on their own is still theoretical, new experimental results indicate that the notion of such algorithms should not be confined to the realm of science-fiction. For example, AI researchers at Facebook and elsewhere have developed algorithms that are capable of cooperating with opponents under controlled experimental conditions. While the development of collusive algorithms in experimental settings does not indicate that they will be used in practice in the near future, consideration of the experimental results along with the rapid pace of technological innovation necessarily raises the question of whether courts have, in the existing body of antitrust law, the tools to reasonably respond to the use of collusive algorithms. This article will briefly discuss three potential legal frameworks for antitrust enforcement related to the use of collusive algorithms.

1. Per Se Illegality for Certain Algorithms

At least one author has proposed that the use of certain algorithms should be deemed a per se antitrust violation. Joseph Harrington argues that although pricing algorithms produce some procompetitive efficiency benefits, the set of algorithmic features that provide efficiency benefits are separate and distinct from the set of algorithmic features that could be used to facilitate collusion. As a result, Prof. Harrington proposes that a set of algorithmic features be constructed that includes features designed to facilitate collusion, and excludes features designed to promote efficiency. To the extent this is possible, Prof. Harrington argues that the collusive algorithmic features can then be deemed per se illegal.

One obstacle to the adoption of a per se rule for certain algorithmic features arises from the traditional approach of federal courts in adopting a rule of per se illegality – that such a rule should only be adopted after courts have gained considerable judicial experience with the challenged conduct. Indeed, the trend in federal courts has been one of limiting the use of the per se rule rather than expanding it. Since there have not yet been any instances of alleged collusive price-fixing by pricing algorithms, it seems quite possible that U.S. courts, at least, would be hesitant to declare a particular algorithmic feature illegal per se without a good deal more experience in this area.

An additional complication to any effort to identify a set of algorithmic features designed to facilitate collusion is the development of advanced AI technologies that will complicate efforts to decode algorithms in the search for evidence of anticompetitive intent. New AI approaches known as neural networks or deep-learning systems attempt to imitate the human brain’s cognitive processes, and have succeeded in beating humans in complex games such as No-Limit Texas Hold’em and Go. The complex structure of deep-learning AI systems may greatly complicate any attempt to retrospectively determine whether an anticompetitive purpose motivated a particular pricing strategy.

2. Algorithmic Tacit Collusion as Evidence of an Agreement

While a § 1 plaintiff must prove that there was an agreement among the defendants, the agreement need not be formal, and there is no requirement that a plaintiff produce direct evidence of the agreement. That said, conscious parallelism alone has historically been insufficient to show an unlawful agreement in violation of § 1.
The facts of *Interstate Circuit v. United States*, in particular, may provide a useful analogue to a theoretical case of algorithmic tacit collusion. In *Interstate Circuit* a dominant Texas first-run movie theater owner sent a letter to eight film distributors, listing each of the distributors on the letter, and requesting that each distributor agree to require minimum prices on later-run films and to prohibit theaters from offering double features.\(^{17}\) Although the eight film distributors did not discuss the arrangement with one another, each adopted the theater owner’s proposal.\(^{18}\) The trial court considered the conduct a conspiracy among the distributors, condemned the arrangement as a §1 violation, and the Supreme Court affirmed.\(^{19}\)

One set of conditions that may be particularly conducive to algorithmic collusion includes (1) the ability of competitors to decode each other’s pricing algorithms and (2) a competitor’s ability to modify their own pricing algorithm in response.\(^{20}\) Under such conditions a firm can begin using a pricing algorithm knowing that competitors will be able to decode it, discover its collusive feature(s), and then decide whether to join in or not. In that respect, introduction of a collusive algorithm is not unlike the hard copy letter sent out inviting competing film distributors to collude in *Interstate Circuit*. This is particularly true if Prof. Harrington is correct that the efficiency-promoting and collusion-promoting features of an algorithm will likely be readily distinguishable from one another.

An additional benefit of considering the use of a particular algorithm as indirect evidence of an agreement to collude is that it may avoid the need to attempt to reverse engineer increasingly complex AI systems, such as neural networks or deep-learning systems. While conclusive evidence that an algorithm was designed to collude would be powerful, such evidence may not be available in cases involving the most advanced AI systems. Dr. Deng notes that in an investigation of the use of collusive algorithms, there are likely to be highly relevant categories of evidence that do not require the technical sophistication needed to decode an algorithm.\(^{21}\) Such information includes communications regarding the goals of an algorithm, the documented behavior of the algorithm, revisions to the algorithm, or promotional material related to the capabilities of an algorithm.\(^{22}\)

Finally, there is experimental evidence indicating that, at least at this stage in development, the ability of algorithms to cooperate is significantly enhanced when multiple competitors use the same algorithm.\(^{23}\) Depending on how development of pricing algorithms proceeds, particularly with respect to the variety of different algorithms are available to firms, their comparative effectiveness, and the ease with which collusive features can be identified, it seems plausible that the use of the same pricing algorithm by competitors might ultimately be the sort of behavior from which an agreement can be inferred.

### 3. An Expanded Role for §5 of the FTC Act

Prof. Harrington and Profs. Ezrachi and Stucke both point to §5 of the FTC as a potential framework for antitrust enforcement to deter the use of collusive algorithms.\(^{24}\) Section 5 of the FTC Act prohibits “unfair methods of competition in or affecting commerce, and unfair or deceptive acts or practices in or affecting commerce.”\(^{25}\) Notably, the requirement that an agreement exist is absent from §5, raising the possibility that it could be applied to address unilateral adoption of collusive algorithms. Second Circuit precedent addressing the proper application of §5 indicates that in the absence of an agreement, “unfair” conduct within the scope of §5 should show “indicia of oppressiveness . . . such as (1) evidence of anticompetitive intent or purpose on the part of the producer charged, or (2) the absence of an independent legitimate business reason for its conduct.”\(^{26}\) Thus, evidence that an algorithm was developed to collude could prove conclusive, even in the event that it is developed and used in a completely unilateral manner.
While the potential application of § 5 of the FTC Act may create broader liability for using algorithms that enable tacit collusion, the extent to which this development would represent bad news for defendants is limited. There is no private right of action under § 5 of the FTC Act, and the only remedies available to the FTC are injunctive in nature. In these respects, the cost of overdeterrence is much lower than in a private treble damages action or Justice Department action.

1 Jon M. Woodruff is an Associate at Stinson Leonard Street LLP in Minneapolis.
2 Ai Deng, What Do We Know About Algorithmic Tacit Collusion?, ANTITRUST, Fall 2018, at 88–85.
3 Id. at 89–90.
4 Id. at 90–93 (discussing several challenges involved in using a collusive algorithm in complex, real-world markets).
6 Id. at 31.
7 Id. at 27.
8 Id. at 24–31.
10 See, e.g., Leegin, 551 U.S. at 907 (holding that vertical price restraints are no longer subject to a per se rule of illegality, and are instead to be evaluated according to the rule of reason).
11 Harrington, supra note 4, at 39.
13 Id. at 25.
14 Bell Atl. Corp. v. Twombly, 550 U.S. 544, 556 (2007) (“[S]tating such a claim requires a complaint with enough factual matter (taken as true) to suggest that an agreement was made.”).
15 Am. Tobacco Co. v. United States, 328 U.S. 781, 809–10 (1946) (“No formal agreement is necessary to constitute an unlawful conspiracy. Often crimes are a matter of inference deduced from the acts of the person accused and done in pursuance of a criminal purpose. . . . The essential combination or conspiracy in violation of the Sherman Act may be found in a course of dealings or other circumstances as well as in any exchange of words.”); Interstate Circuit v. United States, 306 U.S. 208, 221–27 (1939); see also Herbert Hovenkamp, FEDERAL ANTITRUST POLICY § 4.6a (5th ed. 2016).
18 Id. at 218–19.
19 Id. at 232.
20 Deng, supra note 1, at 92.
21 Id. at 91.
22 Id.
23 Id. at 90.
24 Harrington, supra note 4, at 36–38; Ezrachi & Stucke, supra note 8, at 21.
26 E.I. du Pont de Nemours & Co. v. F.T.C., 729 F.2d 128, 139 (2d Cir. 1984).
28 Hovenkamp, supra note 14, § 4.6d.
Algorithms have been used to set prices in some industries for decades. Airlines pioneered the use of yield management pricing – one early type of pricing algorithm – in the 1980s, and related industries including hotels and rental cars soon followed suit. As the use of pricing algorithms has become increasingly widespread in recent years, the antitrust community has taken notice. The OECD held a roundtable discussion on antitrust issues raised by pricing algorithms in 2017, and the FTC recently held a hearing on “Algorithms, Artificial Intelligence and Predictive Analytics.” This article explores how algorithmic pricing differs from traditional pricing practices and how these differences affect competitive outcomes.

A pricing algorithm is an automated procedure for setting prices. As part of the process of selecting a price, an algorithm might monitor competitors’ prices, react to changes in competitors’ prices, predict how competitors will respond to the selected price, and account for factors such as demand conditions, capacity, inventory and costs. Of course, humans who set prices the old-fashioned way often consider all of these factors and more. Algorithms surpass humans, however, in four important ways: they can digest larger volumes of information, process this information with greater speed, execute instructions more reliably and even devise better ways of solving problems than their human counterparts. Each of these advantages can affect the likelihood and effectiveness of coordinated behavior. Because the advantages interact with competitive dynamics in complicated ways, their total impact could make coordination either more or less likely. In short, there is no straightforward prediction that algorithms are good or bad for competition.

The Data Advantage

Transparency in pricing is often cited as a factor that makes coordination more likely. For this reason, the existence of a large number of prices (such as in the cruise line industry) has traditionally been viewed as a barrier to coordination because pricing analysts can only monitor a limited number of prices. Pricing algorithms, however, can compile, standardize and analyze vast quantities of data. The lower cost of monitoring large amounts of prices tends to increase transparency and the likelihood of coordination.

At the same time, the data-crunching power of algorithms makes it easier for firms to generate more prices for their own products, for example, by offering different prices to customer groups based on their purchasing history and demographic characteristics. Moreover, new prices can be set in ways that are harder for competitors to monitor. For example, the price a given customer pays for a product on Jet.com depends on where she lives and what other items are in her cart when she checks out, resulting in thousands of potential price points for a single product. The lower cost of setting a large number of prices tends to decrease transparency and the likelihood of coordination.

Thus, the ability of algorithms to process large amounts of data has two counterbalancing effects on price transparency and the potential for collusion. Which effect dominates will depend on the specific circumstances in which this algorithm is applied.

The Speed Advantage

When firms successfully coordinate, they earn higher profits compared to when they charge competitive prices. Even so, each firm is tempted to defect from the coordinated price by undercutting its rivals and earning even higher profits than it can obtain at the coordinated price. The strength of this temptation depends on how long it takes the other firms to retaliate with lower prices of their own. The longer it takes
rivals to respond, the higher the rewards to defection. Processors in modern personal computers can execute billions of instructions per second, allowing even data-intensive algorithms to set large numbers of prices almost instantaneously. By enabling firms to detect and respond to changes in competitor prices with greater speed, pricing algorithms can decrease the rewards of defection and increase the stability of coordination.

Just because algorithms can make decisions more quickly than humans doesn’t mean that their use will actually result in more frequent price changes. Instead, the result will depend on industry-specific factors. In the e-commerce industry, prices can be changed with little cost, and algorithms can allow prices to be updated with each pageview. In other industries, other constraints limit the pace of change, such as customer contracts or menus that are costly to update. As a result, prices will change less frequently in these industries whether or not algorithms are used.

High-frequency pricing can also have beneficial effects. Adjusting prices in response to changing demand conditions, as in peak-load pricing in the electricity industry, can improve economic efficiency in two ways. First, it ensures that products are allocated to customers who value them the most during periods of high demand. And second, it encourages more flexible customers to substitute their consumption from high-demand periods to low-demand periods. When considering the impact of high-frequency pricing on consumer welfare, these potential improvements in resource allocation need to be weighed against any stabilizing effects on coordinated activity.

The Reliability Advantage

Algorithms deliver consistent results. Unlike humans, who occasionally make mistakes and are subject to emotions that can affect their decisions, an algorithm will time and again produce the same result from a given set of inputs. If firms know their rival’s prices are set by humans who are prone to mistakes, they can’t be certain whether a competitor’s low price is a deliberate attempt to defect or simply a mistake. This uncertainty also makes it more difficult for firms to predict how rivals will respond to their own prices. By reducing (or even eliminating) the error rate in pricing decisions, the widespread use of algorithms can make it easier for firms to detect and punish defection and predict each other’s price responses. This reduction in uncertainty tends to stabilize coordination.

While algorithms execute instructions with great reliability, they are still subject to design errors – commonly referred to as bugs – introduced by their human programmers. Bugs can lead to unpredictable behavior that can destabilize coordination. As algorithms become more complex, bugs tend to multiply and become more difficult to remove.

The Ingenuity Advantage

Beyond simply providing consistent results, algorithms can potentially be more effective at solving complicated problems than their human counterparts. Algorithms using artificial intelligence have already surpassed human capabilities in the domains of chess and poker. Likewise, artificial intelligence algorithms may prove more effective at devising strategies to sustain high prices. Algorithmic ingenuity, however, cuts both ways. As mentioned above, defecting from coordination can be highly profitable if lower prices enable the defector to steal significant sales from its competitors. Algorithms may learn to defect in ways that are more difficult to detect, and thus more profitable, just as they have learned to bluff in poker. At the end of the day, algorithms still face the fundamental prisoner’s dilemma that so frequently undermines coordination, and there is no guarantee that simply introducing more sophisticated players will result in more successful coordination.
Conclusion

Pricing algorithms have four important advantages over human analysts: data, speed, reliability and ingenuity. Each of these advantages helps firms better optimize their pricing decisions. At the same time, the advantages also affect the incentive and ability to coordinate in a number of ways. Some of these effects increase the risk of coordination, while others decrease it. Only by evaluating the specific characteristics of a particular pricing algorithm and the industry in which it is used can these opposing effects be properly weighed against each other.

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1 Dr. Tim Watts is a Managing Director at NERA Economic Consulting. The opinions expressed in this article are those of the author and do not necessarily reflect the views of the firm or its clients.
3 Horizontal Merger Guidelines Section 7.2.
4 Anne D’Innocenzio, “Jet.com’s Marc Lore is out to reinvent the shopping cart,” AP News May 16, 2016 https://apnews.com/e7eba4c9f0ef4d38ad9e767bc5c28291.
5 This assumes the algorithm is designed to be deterministic rather than probabilistic. Even probabilistic algorithms, such as random number generators, maintain a stable distribution of outcomes.