Tacit Agreements to Collude: Enforcing Section 1 of the Sherman Act in the Age of Algorithms

BY DAVID O. FISHER

ASTROLOGISTS, NEW AGE PHILOSOPHERS, and rock-musical composers have long heralded the dawning of the Age of Aquarius, an astrological era in which mankind will be guided by the principles of harmony, egalitarianism, and understanding. But computer scientists, business experts, and cultural observers have more recently signaled the dawning of another new era—the Age of Algorithms—in which our markets, institutions, and behaviors are guided by increasingly complex and pervasive automated systems. For the antitrust community, the dawning of the Age of Algorithms is synonymous with the rise of algorithmic pricing. While airlines, hotels, and others have been using yield-management software for decades, the last twelve years have seen an explosion in the use and sophistication of pricing algorithms, most notably by online platforms and in housing, ride sharing, and online retail markets.[1]

Proponents of algorithmic pricing contend that it creates efficiencies that give rise to procompetitive effects.[2] Some empirical evidence suggests that, by allowing price adjustments based on real-time data, landlords' use of pricing algorithms can make rental prices more responsive to market conditions, which can lead to lower rents during economic downturns.[3] Some theoretical models also suggest that, by improving projections using more and higher quality data, pricing algorithms may encourage firms to cheat on a cartel price by deviating prices downward during times of high predicted demand.[4] Some also argue that algorithmic pricing may promote non-price competition, reduce waste, and lower operational costs, which could conceivably drive down prices and reduce entry barriers, although these claims are not supported by evidence.[5]

It is highly unlikely that all of these claims of procompetitive effects are true. First, algorithmic-pricing tools are marketed and sold as revenue-maximization tools.[6] No pricing tool could be profitable if it reduces prices in all demand conditions. Second, and more importantly, theoretical models which link algorithmic pricing with increased price competition defy empirical reality, including because they ignore the effects of market power. Empirical evidence shows that, when real pricing algorithms are used in real markets, the lower prices they produce are short lived, giving way to higher prices over time.[7] This evidence supports the very real concern that pricing algorithms are used to implement express collusion or facilitate tacit collusion.[8]

Understanding Algorithmic Collusion

"Algorithmic collusion" refers to a number of distinct but overlapping ways in which pricing algorithms may allow competitors to undermine price competition. Some use the term as a synonym for autonomous algorithmic collusion, in which AI-powered algorithms "learn" to avoid competition without being explicitly instructed to do so.[9] Early empirical work focused on the use of Q-learning, a model-free reinforcement learning algorithm in which an agent learns how to make the best decisions through trial and error.[10] More recent work has focused on the use of pricing agents based on large language models ("LLM"), a form of generative AI which is trained using self-supervised machine learning on massive amounts of text data to carry out human-like language processing tasks. LLM-based pricing agents are increasingly popular because they are much cheaper and more accessible to businesses than other models.[11]

Empirical work has shown that both Q-learning and LLM-based pricing algorithms consistently learn to charge supracompetitive prices on their own, without being programmed to do so and without communicating with each other about pricing strategy.[12] While there is not yet a consensus about whether autonomous algorithmic collusion can be addressed by existing antitrust laws this growing body of research suggests that machine-learning makes algorithms particularly susceptible to collusive pricing, particularly in oligopoly settings, and that AI-powered algorithmic pricing should prompt us to revisit assumptions about the self-correcting power of markets, the error costs of false negatives, and the element of agreement under Section 1.[13]

A more straightforward form of algorithmic collusion is explicit algorithmic collusion, when the users of an algorithm expressly agree to collude, and the algorithm simply serves as a tool to execute the agreement.[14] The primary case exemplifying this form of algorithmic collusion is *United States v. Topkins*, in which an Amazon seller of posters pleaded guilty to forming a horizontal price-fixing agreement with his competitors by writing computer code that

David O. Fisher is Senior Counsel at the American Antitrust Institute. The author would like to thank Randy Stutz and Christopher R. Leslie for their important contributions to this piece.

instructed dynamic pricing algorithms to set prices in conformity with the agreement.[15]

The third and, so far, most-litigated form of algorithmic collusion is the use of an algorithmic cartel manager.[16] In this form of collusion, competitors coordinate pricing decisions by relying on a shared pricing algorithm as an intermediary which collects each competitors' information and sets pricing rules.[17] A rich body of empirical research suggests that competitors' use of the same pricing software can give rise to supracompetitive prices, even in the absence of express agreements to collude, by enabling competitors to shift from individual profit-maximizing strategies to joint profit-maximizing strategies.[18]

Online platforms are uniquely well suited to serving as cartel managers because they have access to each participant's pricing data and can use rules to limit price competition without requiring an express horizontal agreement among platform participants.[19] In *Meyer v. Kalanick*, for example, the Southern District of New York held that Uber customers had plausibly alleged that the app's pricing algorithm facilitated horizontal price fixing in violation of Section 1 by preventing Uber drivers from competing on price and by using surge pricing to artificially reduce demand and keep prices high.[20]

The use of an algorithmic cartel manager has important parallels to information-sharing. This was the conduct at issue in *United States v. Agri Stats*. In that case, a Minnesota federal court held that the Department of Justice and six states plausibly alleged that Agri Stats enables horizontal price fixing and output restrictions in the pork, chicken, and turkey processing industries.[21] Although *Agri Stats* does not involve allegations of algorithmic pricing, it and other information-sharing cases establish that sharing sensitive pricing information with a common intermediary can violate Section 1, particularly when the pricing information is granular, non-anonymous, non-public, or forward-looking.[22]

To date, cases alleging the use of an algorithmic cartel manager have been brought in housing markets (*In re RealPage* and *Duffy v. Yardi*), hotel markets (*Gibson v. Cendyn* and *Cornish-Adebiyi v. Caesars*), and the health insurance reimbursement market (*In re MultiPlan*).[23] In each case, plaintiffs alleged a hub-and-spoke conspiracy in which competitors (the spokes) fed their non-public data to a central algorithmic pricing provider (the hub) and accepted the prices it recommended, resulting in more vacant units and higher prices (in the housing and hotels cases) and lower reimbursement rates (in *MultiPlan*). In each case, the main issue presented was whether the competitors' conduct permits the inference of a horizontal agreement between the competitors (the rim).

Each case turned on whether the plaintiff pleaded sufficient plus factors—circumstantial evidence that indicates that the defendants colluded, such as high market concentration or the exchange of pricing information—to support the inference of a horizontal rim agreement.[24] In the hotel cases, both district courts found insufficient plus factors because the hotels started using the common algorithm years apart, did not directly share data with each other, and did not promise to accept the algorithm's recommendations in all cases.[25]

In contrast, the courts in the housing cases inferred a horizontal rim agreement because the landlords acted against their self-interest in two ways. First, they gave non-public pricing and occupancy data to a third party they knew was making pricing recommendations to their competitors. Second, they raised prices even when doing so meant leaving housing units unoccupied, reducing output in a way that firms don't usually do unless they are colluding.[26] The court in *MultiPlan* similarly found that the insurers acted against their self-interest by paying below-market reimbursement rates to providers and sharing competitively sensitive pricing information with their competitors through the third-party hub.[27]

Both courts in the hotel cases and the court in *MultiPlan* also found that the lack of other plus factors was not controlling considering how the relevant algorithms worked. Because the algorithms recommend prices to each competitor based on the non-public information of the others, it did not matter that the competitors did not share information directly with each other; they still benefited from each other's non-public information through their use of the algorithmic hub.[28] And although the algorithms' recommendations were discretionary, they adopted them most of the time, and frequently enough to reduce output and raise prices above competitive levels.[29] The courts did not consider timing a decisive factor, even though the landlords started using the algorithm at different points over several years.

Assessing Algorithmic Collusion

Pricing algorithms present a challenge for courts because they have novel capabilities that enable tacit agreement in circumstances where it was not previously possible. Their ability to make complex decisions based on large inputs of segregated data enables firms to make decisions based on each other's data without ever communicating or sharing data with each other. Moreover, they constantly update their outputs in real time based on each new input, meaning that firms can benefit from each other's data even when they start using the algorithm years apart, and without monitoring each other's behavior. Courts' analyses in algorithmic cartel manager cases suggest at least three conclusions about how the law can account forthese novelties.

First, the absence of plus factors such as direct communication, information sharing, and simultaneous conduct does not make an inference of agreement unreasonable. Courts have long recognized plaintiffs' individual allegations of a conspiracy should not be compartmentalized, and that the plus-factor analysis should be holistic, with no one plus factor being required to infer an agreement.[30] In addition, plus factors have synergistic probative value, such that each additional plus factor reinforces the strength of the inference suggested by the others.[31] This suggests that, when sufficient plus factors are present, the absence of others does not make the inference unreasonable.[32]

Second, plus factors that suggest firms are acting against their independent self-interest are particularly probative of agreement.[33] The Supreme Court has recognized that the purpose of Section 1 is to ensure independent centers of economic decision-making.[34] Yet economic evidence demonstrates that shared algorithmic pricing tools may encourage firms to make pricing decisions that are joint profit maximizing.[35] This suggests that courts should give particular weight to those plus factors that suggest firms are acting in ways that are not consistent with their independent self-interest, such as reducing output in times of high demand.[36]

Finally, the characteristics that enable pricing algorithms to facilitate stable tacit agreements can be plus factors. Courts have recognized that there is no finite list of plus factors, and the list of plus factors must expand as technologies evolve.[37] Over the past fifty years, computer scientists have developed techniques that allow algorithms to create stable agreements, including digital signatures, cryptography, broadcasting, communication over private channels, and leader election, wherein one agent is selected as the organizer of a particular task.[38] Although broadcasting (in the form of regular communication between cartel members) and leader election (in the form of a cartel manager) are accounted for in the existing plus-factor analysis, technology experts suggest that courts and enforcers should add the use of digital signatures, cryptography, and private channels to the list of plus factors that may indicate the existence of algorithmic collusion.[39]

Prohibiting Tacit Agreements to Collude

Faced with the realities of algorithmic pricing, some antitrust scholars contend that antitrust law must adapt by rehabilitating tacit agreement as a theory of Section 1 liability and expressly prohibiting algorithmic tacit collusion.[40] Although tacit agreements to fix prices are in principle illegal under Section 1, they have become increasingly difficult to prove because of steadily heightening evidentiary standards premised on long-held assumptions that oligopolies are more likely to engage in interdependent pricing than to collude and that cartel agreements by nature are unstable.[41] But contemporary economic scholarship suggests these assumptions are mistaken, and evidence shows that market concentration is associated with higher prices and long-lasting, durable cartels.[42] Pricing algorithms, which use methods that computer scientists have developed over decades to allow for stable agreements among disparate actors, and which use opaque methods to adopt joint profit maximization strategies and "learn" on their own to collude, further undermine those assumptions, reducing the likelihood of false positives and raising the costs of false negatives.[43]

Long before the dawning of the Age of Algorithms, eminent scholars including Judge Richard Posner argued that oligopoly pricing is properly understood as an illegal tacit agreement under Section 1: one oligopolist's price increase is an implicit offer, which the others implicitly accept by matching; and, recognizing the potential for mutual benefit, the parties perform by collectively maintaining supracompetitive prices. Other eminent scholars, including former DOJ Antitrust Division head Donald Turner, emphasized that there is no effective legal remedy for oligopoly pricing because there is no discernable act that a court could enjoin; judges are not equipped to set and regulate "reasonable" market prices, and they cannot order firms not to react to their competitors' prices. Courts have tenuously resolved this debate by inferring a tacit agreement only when the defendants engage in communication, information sharing, or other conduct that can be enjoined.[44] In cases where an algorithmic hub serves as a cartel manager, couldn't courts similarly enjoin the use of shared pricing algorithms that facilitate oligopoly pricing? At least in some circumstances, one would think so.

Pricing algorithms continue to increase in sophistication and prevalence throughout our economy, and courts are likely to be grappling with algorithmic collusion for some time. Like the Age of Aquarius, it's not clear whether the true dawning of the Age of Algorithms is still to come or has already arrived. Regardless, we must be ready to adapt our application of antitrust law accordingly. ■

1 *See* Wedad Elmaghraby & Pinar Keskinocak, *Dynamic Pricing in the Presence of Inventory Considerations: Research Overview, Current Practices, and Future Directions*, 49 Mgmt. Sci. 1287, 1288 (2003); Dan Hill, *The Secret of Airbnb's Pricing Algorithm: The sharing economy needs machine intelligence to set prices*, IEEE Spectrum (Aug. 20, 2015), https://spectrum.ieee.org/the-secret-of-airbnbs-pricing-algorithm; Le Chen et al., *An Empirical Analysis of Algorithmic Pricing on Amazon Marketplace*, *in* WWW'16: Proceedings of the 25th Int'l Conf. on World Wide Web 1339, 1344–45 (J. Bourdeau et al. eds., 2016) available at https://mislove.org/publications/Amazon-WWW.pdf; Zach Y. Brown & Alexander MacKay, *Competition in Pricing Algorithms* 15 Am. Econ. J.: Microeconomics 109, 122 (2023), *available at* https://doi.org/10.1257/mic.20210158; Sophie Calder-Wang & Gi Heung Kim, Algorithmic Pricing in Multifamily Rentals: Efficiency Gains or Price Coordination? 30, 57 (Aug. 16, 2024) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4403058; Peter Cohen et al., *Using Big Data to Estimate Consumer Surplus: The Case of Uber* 3–4 (Nat'l Bureau of Econ. Rsch., Working Paper 22627, 2016), https://doi.org/10.3386/w22627.

2 *See, e.g.*, Lawrence Zhang, *Comments to Competition Bureau of Canada Regarding Algorithmic Pricing and Competition*, Info. Tech. & Innovation Found. (Aug. 8, 2025), https://itif.org/publications/2025/08/08/comments-competition-bureau-of-canada-regarding-algorithmic-pricing-competition/

3 Calder-Wang & Kim, *supra* note 1, at 16–17.

4 Jeanine Miklós-Thal & Catherine Tucker, *Collusion by Algorithm: Does Better Demand Prediction Facilitate Coordination Between Sellers?*" 65 Mgmt. Sci. 1552, 1560 (2019).

5 *See, e.g.*, Gonenc Gurkaynak, *Algorithms and Artificial Intelligence: An Optimist Approach to Efficiencies* 5 Competition Law & Policy Debate J. 29 (2019), available at https://ssrn.com/abstract=3783353; OECD (2017); "Algorithms and Collusion: Competition Policy in the Digital Age", *OECD Roundtables on Competition Policy Papers*, No. 206, OECD Publishing, Paris, at pp.14–18, 21, https://doi.org/10.1787/258dcb14-en.

6 *See, e.g.*, *Cendyn Guestrev*, CENDYN, https://www.cendyn.com/guestrev/ (last accessed Sept 12, 2025) (advertising algorithmic pricing product as a means for hotels and casinos to "[s]upercharge profit" and "maximize revenue"); *Revenue IQ,* YARDI, https://www.yardi.com/product/revenue-iq/ (last accessed Sept 12, 2025) (advertising algorithmic pricing product as helping residential landlord clients "[a]chieve [their] revenue goals").

7 Calder-Wang, *supra* note 2, at 30–31; Leon Musolff, Algorithmic Pricing, Price Wars and Tacit Collusion: Evidence from E-Commerce 1–2 (Mar. 27, 2024), available at https://lmusolff.com/papers/Algorithmic_Pricing.pdf.

8 Christopher R. Leslie, *Predatory Pricing Algorithms,* 98 N.Y.U.L. REV. 49, 52 n.7 (2023); Kevin T. White & Tammy W. Cowart, Behind the Cloaking Device: *Is There an Anti-Competitive Agreement Lurking Under the Use of Common Pricing Algorithms By Multifamily Landlords?*, 63 WASHBURN L.J. 287, 299–319 (2024).

9 Ibrahim Abada et al., Algorithmic Collusion: Where Are We and Where Should We Be Going? 14–18 (Aug. 1, 2025) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4891033.

10 Emilio Calvano et al., Artificial Intelligence, Algorithmic Pricing, and Collusion 35–36 (Dec. 11, 2019) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3304991.

11 Sara Fish et al., Algorithmic Collusion by Large Language Models 23–24 (May 22, 2025) (unpublished manuscript), https://doi.org/10.48550/arXiv.2404.00806.

12 *Id*. Abada et al., *supra* note 9, at 2–3; *Id*. at 23–24; Calvano et al., *supra* note 10, at 35–36.

13 *See* David O. Fisher, Cleaning and Sharpening Our Antitrust Tools for the Age of AI, AMERICAN ANTITRUST INSTITUTE (Mar. 5, 2025), https://www.antitrustinstitute.org/wp-content/uploads/2025/03/AAI-Commentary-Algorithmic-Pricing.pdf.

14 Michal S. Gal, *Limiting Algorithmic Coordination*, 38 BERKELEY TECH. L.J. 173, 181 (2023).

15 Press Release, U.S. Dep't Just., Former E-Commerce Executive Charged with Price Fixing in the Antitrust Division's First Online Marketplace Prosecution (Apr. 6, 2015), https://www.justice.gov/opa/pr/former-e-commerce-executive-charged-price-fixing-antitrust-divisions-first-online-marketplace.

16 Herbert Hovenkamp, Christopher R. Leslie, *The Firm as Cartel Manager*, 64 Vand. L.R. 813, 843 (2011) (examining cartel structure involving "the transfer of daily authority from the cartel's members as a group to . . . a third-party organization that has the power to control the cartel members' individual output and prices").

17 Martin Spann et al., *Algorithmic Pricing: Implications for Marketing Strategy and Regulation*, INT'L J. OF RSCH. IN MKTG. 12 (May 30, 2025), https://doi.org/10.1016/j.ijresmar.2025.05.001.

18 Calder-Wang & Kim, *supra* note 1, at 28–31; Musolff, *supra* note 7, at 1–2.

19 *See* Chen et al., *supra* note 2, at 1340–41, 1344.

20 174 F. Supp. 3d 817, 822–28 (S.D.N.Y. 2016).

21 *United States v. Agri Stats, Inc.*, No. 23-cv-3009-JFD-JRT, 2024 U.S. Dist. LEXIS 94142 (D. Minn. May 28, 2024).

22 Statement of Interest of the United States, *In re Pork Antitrust Litigation*, 495 F. Supp. 3d 753 (D. Minn., filed Oct. 1, 2024).

23 *In re RealPage, Inc.*, 709 F.Supp.3d 478 (M.D. Tenn. 2023); *Duffy v. Yardi Systems, Inc.*, 758 F.Supp.3d 1283 (W.D. Wash. 2024); *Gibson v. Cendyn Grp.*, No. 2:23-cv-00140-MMD-DJA, 2024 U.S. Dist. LEXIS 83547 (D. Nev. May 8, 2024), appeal docketed, No. 24-3576 (9th Cir. June 7, 2024); *Cornish-Adebiyi v. Caesars Ent. Inc.*, No. 1:23-cv-02536-KMW-EAP, 2024 U.S. Dist. LEXIS 178504 (D.N.J. Sept 30, 2024), appeal docketed, No. 24-3006 (3rd Cir. Oct. 29, 2024); *In re Multiplan Health Ins. Provider Litig.*, No. 24-cv-6795, 2025 U.S. Dist. LEXIS 104989 (N.D. Ill. June 3, 2025).

24 Christopher R. Leslie, *The Probative Synergy of Plus Factors in Price-Fixing Litigation*, 115 NW. U.L. REV. 1581, 1586, 1590–91, 1597 (2021).

25 *Cendyn*, *supra* note 22, at *7–28; *Caesar's*, *supra* note 22, at *7–22. A panel of judges on the Ninth Circuit affirmed the district court's holding in *Gibson v. Cendyn* after plaintiffs abandoned their appeal of the hub-and-spoke claim. *Gibson v. Cendyn Grp., LLC*, 148 F.4th 1069, 1077, 1081 (9th Cir. 2025).

26 *RealPage, supra* note 22, at 509–13, 516–18; *Yardi, supra* note 22, at 1292–94.

27 *Multiplan*, *supra* note 22, at *72–74.

28 *Id.*; *RealPage*, *supra* note 22, at 511–13; *Yardi*, *supra* note 22, at 1293.

29 *Multiplan*, *supra* note 22, at *63–64; *RealPage*, *supra* note 22, at 534–35; *Yardi*, *supra* note 22, at 1293–94.

30 *Cont'l Ore Co. v. Union Carbide & Carbon Corp.*, 370 U.S. 690, 698 (1962).

31 Leslie, *supra* note 23, at 1587–88.

32 *See generally* Christopher R. Leslie, *The Factor/Element Distinction in Antitrust Litigation*, 64 WM & MARY L. REV. 585 (2023).

33 *See, e.g.*, *In re Pool Prods. Distrib. Market Antitrust Litig.*, 988 F. Supp. 2d 696, 711 (E.D. La. 2013) ("A plausible allegation that the parallel conduct was not in the alleged conspirators' independent self-interest absent an agreement is generally considered the most important 'plus factor.'").

34 *Copperweld Corp. v. Indep. Tube Corp.*, 467 U.S. 752, 769 (1984).

35 Calder-Wang & Kim, *supra* note 1, at 28–31; Musolff, *supra* note 7, at 1–2.

36 Leslie, *supra* note 23, at 1616–17; PHILLIP E. AREEDA & HERBERT HOVENKAMP, ANTITRUST LAW § 1408e n.21 (4th ed. 2024).

37 *In re Flat Glass Antitrust Litig.*, 385 F.3d 350, 360 (3d Cir. 2004)

38 Giovanna Massarotto, *Detecting Algorithmic Collusion*, 86 OHIO STATE L.J. (forthcoming 2025) (manuscript at 5), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5191297.

39 *Id.* at 32–33.

40 Isaac Appel, *Economic Terminators: The Futility of American Antitrust Law in an AI-driven Economy*, 50 J. CORP. L. 209, 224–29 (2024); Ariel Ezrachi & Maurice E. Stucke, *Sustainable and Unchallenged Algorithmic Tacit Collusion*, 17 NW. J. TECH & INTELL. PROP. 217, 258–59 (2020).

41 Christopher R. Leslie, *The Decline and Fall of Circumstantial Evidence in Antitrust Law*, 69 AM. U. L. REV. 1713 (2020); William H. Page, *Tacit Agreement Under Section 1 of the Sherman Act*, 81 ANTITRUST L.J. 593 (2017); ROBERT H. BORK, THE ANTITRUST PARADOX: A POLICY AT WAR WITH ITSELF 196 (1978); RICHARD A. POSNER, ANTITRUST LAW: AN ECONOMIC PERSPECTIVE 53 (1976).

42 Jonathan B. Baker, *Taking The Error Out of "Error Cost" Analysis: What's Wrong With the Antitrust's Right*, 80 ANTITRUST L.J. 1, 12–13 (2015); Christopher R. Leslie, *Antitrust's Interdependence Paradox*, 111 VA. L. REV. 787 (2025).

43 Massarotto, *supra* note 37; Calder-Wang & Kim, *supra* note 1, at 28–31; Musolff, *supra* note 7, at 1–2; Fish, et al., *supra* note 11, at 23–24; Michal S. Gal & Jorge Padilla, *A General Framework for Analyzing the Effects of Algorithms on Optimal Competition Laws*, 26 THEORETICAL INQUIRIES IN L. 183, 205–26 (2024).

44 ANDREW I. GAVIL et al., *Sidebar 3-2: The Turner/Posner debate on Conscious Parallelism*, *in* ANTITRUST LAW IN PERSPECTIVE: CASES, CONCEPTS AND PROBLEMS IN COMPETITION POLICY 302–05 (5th ed. 2024).