

Algorithmic Pricing: What Every Antitrust Lawyer Needs to Know

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Overview

Lawyers and economists have raised concerns that rapid technological development in artificial intelligence, consumer data gathering, and e-commerce might facilitate and exacerbate anticompetitive behavior. In particular, some predict that algorithmic pricing will harm competition and consumers as a result of anticompetitive behavior among competitors (e.g., horizontal price fixing), between suppliers and distributors (e.g., vertical price fixing), and by individual firms (e.g., price discrimination). The COVID-19 pandemic magnified these concerns as consumers increasingly purchased products online, where prices are often determined and monitored by computer algorithms. Although the use of algorithms to monitor and set prices has increased considerably over time, it remains empirically unclear whether algorithmic pricing threatens or benefits market competition. Regardless, lawyers are likely to see regulators apply increased scrutiny where algorithmic pricing is used, resulting in disputes over the effects of algorithmic pricing on markets.

This article explains algorithmic pricing and provides an economic perspective on the potential for algorithmic pricing to facilitate horizontal price fixing, vertical price fixing, and price discrimination. The article also explains the ways in which

algorithmic pricing may in fact enhance competition and consumer welfare.

What is Algorithmic Pricing?

Algorithmic pricing simply means a set of prices determined by a pre-specified set of pricing rules or strategies. Companies have long relied on pricing rules or strategies to guide pricing decisions across business cycles or based on changes in input prices, the prices charged by competitors, or other changes in market conditions. Over time, however, the term algorithmic pricing has been increasingly used to refer specifically to the use of computers to implement a pricing strategy by automatically setting prices without (or with minimal) manual price setting.

Algorithmic pricing has the potential to improve competition and market efficiency. As more commerce shifts to online spaces where price comparisons tend to be relatively easy, it has become easier and cheaper for a firm's pricing algorithm to monitor the prices of suppliers, competitors, and distributors, and to dynamically optimize prices based on supply and demand forecasts.¹ Additionally, with the increased prevalence of free consumer-facing products that can automatically monitor prices across sellers,² firms that use algorithmic pricing to offer the most competitive prices can more easily attract customer attention via their lower prices.

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¹ See Robert M. Weiss & Ajay K. Mehrotra, *Online Dynamic Pricing: Efficiency, Equity and the Future of E-commerce*, 6 VA. J.L. & TECH. 11 (2001); Jeanine Miklós-Thal & Catherine

E. Tucker, *Collusion by Algorithm: Does Better Demand Prediction Facilitate Coordination Between Sellers?*, 65 MGMT. SCI. 1552 (2019).

² See, e.g., Walt Roloson & Adam Gauvin, *Saving Money Online Is Easy, Fast With Wikibuy from Capital One*, *Capital One* (Feb. 27, 2019), <https://www.capitalone.com/tech/software-engineering/saving-money-online-is-easy-and-fast-with-wikibuy-from-capital-one/>; see also Michal S. Gal & Niva Elkin-Koren, *Algorithmic Consumers*, 30 HARV. J.L. & TECH. 309 (2017).

However, algorithmic pricing also has its limitations. In one well-known example, two competing online retailers selling on Amazon Marketplace offered a new version of a commonly referenced biology textbook for approximately \$20 million, although used copies were available for under \$40.³ These high prices were the result of two independent algorithmic pricing strategies that each determined sales price based on the price offered by the other competitor, leading to prices that precluded sales from both retailers. This example highlights the difficulty of designing profitable algorithmic pricing strategies that account for all possible contingencies that firms face in a market.

Algorithmic Pricing and Horizontal Price-Fixing

Horizontal price-fixing occurs when two or more competitors agree upon a pricing strategy. Firms can increase profits by colluding on a horizontal price-fixing scheme that results in higher prices. Successful collusion typically requires complex coordination on both a collusive pricing strategy and the consequences of deviating from that pricing strategy.⁴

Recent growth in public awareness of technology-related issues such as data privacy, predictive algorithms, and targeted marketing has raised

questions from regulators, policymakers, and litigators as to whether firms could use algorithmic pricing to establish and maintain a collusive strategy with or without explicit communication and coordination.⁵ According to some, modern antitrust concerns are “shifting from the world where executives expressly collude in smoke-filled rooms to a world where pricing algorithms continually monitor and adjust to each other’s prices and market data.”⁶

Algorithmic pricing has different potential impacts on explicit and tacit forms of collusion.

Explicit Collusion. For firms that establish a collusive pricing strategy and consequences through explicit agreement (*i.e.*, explicit collusion), algorithmic pricing could make it easier for colluders to automatically adjust prices as expected demand changes and to quickly detect and punish deviations from the collusive pricing strategy without explicit communication (*e.g.*, by reverting to a competitive pricing strategy).⁷ Algorithmic pricing thus could, in theory, reduce the need for individuals in firms to communicate in order to maintain a previously coordinated collusive strategy, which might reduce the evidence available to prove the existence of collusion.⁸ Importantly,

³ Olivia Solon, *How A Book About Flies Came To Be Priced \$24 Million On Amazon*, WIRED (Apr. 27, 2011), <https://www.wired.com/2011/04/amazon-flies-24-million/>.

⁴ Cooper and Kühn (2014) find that a common understanding of how deviations will be punished is essential for sustainable collusive strategies. See David J. Cooper & Kai-Uwe Kühn, *Communication, Renegotiation, and the Scope for Collusion*, 6 Am. Econ. J.: Microeconomics 247 (2014), available at <http://dx.doi.org/10.1257/mic.6.2.247>.

⁵ See, *e.g.*, OECD, *Algorithms and Collusion: Competition Policy in the Digital Age* (Sept. 14, 2017), www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm; *Price-Bots Can Collude Against Consumers*, ECONOMIST (May 6, 2017), <https://www.economist.com/finance-and-economics/2017/05/06/price-bots-can-collude-against-consumers>; Maurice E. Stucke & Ariel Ezrachi, *How Pricing Bots Could Form Cartels and Make Things More Expensive*, HARV. BUS. REV. (Oct. 27, 2016), <https://hbr.org/2016/10/how-pricing-bots-could-form-cartels-and-make-things-more-expensive>.

⁶ Ariel Ezrachi & Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition*, 2017 U. ILL. L. REV. 1775 (2017).

⁷ For colluding partners looking to outsource or simplify the task of developing pricing algorithms to maintain a collusive strategy, these firms could coordinate on their purchase of pricing

algorithms from a third-party “hub,” which in turn could provide algorithms with a preprogrammed collusive strategy.

⁸ See Ulrich Schwalbe, *Algorithms, Machine Learning, and Collusion*, 14 J. COMPETITION L. & ECON. 568 (2018), available at <https://doi.org/10.1093/joclec/nhz004>. In practice, algorithmic pricing does not appear to significantly reduce the need to communicate after a collusive strategy has been agreed upon, as the case of GBE and its competitor Trod demonstrates. Trod and GBE explicitly agreed to match prices on certain products sold through Amazon. But the difficulties of relying on human-set prices to maintain their agreement led them to develop pricing algorithms to set identical prices where there were no lower-price competitors. However, unintentional deviations from the collusive strategy resulted in continued communication between the firms. See Claudia Patricia O’Kane & Ioannis Kokkoris, *A Few Reflections on the Recent Case Law on Algorithmic Collusion*, COMPETITION POL’Y INT’L, ANTITRUST CHRON. (July 13, 2020), <https://dev.competitionpolicyinternational.com/wp-content/uploads/2020/07/7-A-Few-Reflections-on-the-Recent-Case-Law-on-Algorithmic-Collusion-Claudia-Patricia-O%E2%80%99Kane-Ioannis-Kokkoris.pdf>, at 3-4; CMA, *Decision of the Competition and Markets Authority: Online Sales of Posters and Frames, Case 50223* (Aug. 12, 2016), <https://assets.publishing.service.gov.uk/media/57ee7c2740f0b606dc000018/case-50223-final-non-confidential-infringement-decision.pdf>, at 38, 41.

regardless of the impact on evidence of subsequent communications, the choice to collude in such circumstances would be explicit, and evidence of the initial communication establishing the explicit collusive arrangement would remain an important piece of the case.

Tacit Collusion. As a general matter, both U.S. and E.U. statutes require an explicit agreement between the parties to support a finding of horizontal price-fixing.⁹ But lawyers and economists recently have debated whether algorithmic pricing could be used to establish a successful collusive strategy without any explicit agreement (*i.e.*, tacit collusion), which could be difficult or impossible for regulators or market participants to prove.¹⁰ If algorithms can autonomously coordinate, some fear that firms may collude and “leave no trace of concerted action.”¹¹

Most studies to date suggest that it is hard to achieve collusive outcomes spontaneously through pricing algorithms. For example, a 2018 review of computer science and economics literature suggests that implicit collusion among autonomous algorithms or artificial intelligences is not a practical concern given the complexity of colluding among more than two firms and the limited capabilities of algorithmic communication.¹² A new study was able to demonstrate that algorithmic pricing powered by artificial intelligence can result in sophisticated collusive strategies in a variety of simulated environments.¹³ However, findings from a recent

working paper indicate that the likelihood of collusion in these simulations drops considerably as the number of competitors increases or as the ability of these artificial intelligence algorithms to learn becomes more sophisticated.¹⁴ These results suggest that it is unlikely that pricing algorithms will be able to sustain collusive prices in markets with entry over time. Although evidence of autonomous algorithmic pricing collusion is rooted mostly in theory and computer simulations rather in real-world examples,¹⁵ preliminary evidence from the German retail gasoline market suggests that some markets that rely on algorithmic pricing may already have experienced a gradual increase in margins due to tacit collusion.¹⁶

This suggests that, for the time being, the question of intention—and the evidence surrounding that intention—would likely be central to any algorithmic collusion case, in addition to an analysis of prices and output, as well as any effects on innovation. Given the increasing pace of progress in artificial intelligence, the ability of pricing algorithms to tacitly collude is sure to be a subject of continued study and debate.¹⁷

Algorithmic Pricing and Vertical Price-Fixing

Vertical price-fixing occurs when a supplier specifies the prices at which its products can be resold to customers by distributors. The most commonly used mechanism for vertical price-fixing is resale price maintenance (RPM), whereby

⁹ For discussions of the concept of agreement under U.S. and E.U. standards, respectively, see William H. Page, *Communication and Concerted Action*, 38 Loy. U. Chi. L.J. 405 (2007) and Kelvin Hiu Fai Kwok, *The Concept of ‘Agreement’ Under Article 101 TFEU: A Question of EU Treaty Interpretation*, 44 EUR. L. REV. 221 (2019).

¹⁰ See, e.g., Ariel Ezrachi & Maurice E. Stucke, *Sustainable and Unchallenged Algorithmic Tacit Collusion*, 17 NW. J. TECH. & INTELL. PROP. 214 (2020), available at <https://scholarlycommons.law.northwestern.edu/njtip/vol17/iss2/2/>; Kai-Uwe Kühn & Steve Tadelis, *The Economics of Algorithmic Pricing: Is Collusion Really Inevitable?* (Dec. 2018) (unpublished paper, on file with authors).

¹¹ *Id.* at 256.

¹² Ulrich Schwalbe, *Algorithms, Machine Learning, and Collusion*, 14 J. COMPETITION L. & ECON. 568 (2018), available at <https://doi.org/10.1093/joclec/nhz004>.

¹³ Emilio Calvano, Giacomo Calzolari, Vincenzo Denicolò, & Sergio Pastorello, *Artificial Intelligence, Algorithmic Pricing, and Collusion*, 110 AM. ECON. REV. 3267 (2020).

¹⁴ See John Asker, Chaim Fershtman, & Ariel Pakes, *Artificial Intelligence and Pricing: The Impact of Algorithm Design* (NBER Working Paper No. 28535, 2021).

¹⁵ Axel Gautier, Ashwin Ittoo, & Pieter Cleynenbreugel, *AI Algorithms, Price Discrimination and Collusion: A Technological, Economic and Legal Perspective*, 50 EUR. J. LAW & ECON. 405 (2020).

¹⁶ See Stephanie Assad, Robert Clark, Daniel Ershov, & Lei Xu, *Algorithmic Pricing and Competition: Empirical Evidence from the German Retail Gasoline Market* (CESifo Working Paper No. 8521, 2020), <https://www.cesifo.org/en/publikationen/2020/working-paper/algorithmic-pricing-and-competition-empirical-evidence-german>.

¹⁷ See, e.g., Ariel Ezrachi & Maurice E. Stucke, *Sustainable and Unchallenged Algorithmic Tacit Collusion*, 17 NW. J. TECH. & INTELL. PROP. 214 (2020), available at <https://scholarlycommons.law.northwestern.edu/njtip/vol17/iss2/2/>.

suppliers and distributors come to an understanding that restricts the prices that distributors can charge.¹⁸ Unlike horizontal price-fixing, which is generally viewed as having anticompetitive effects, RPM is recognized to have both procompetitive and anticompetitive justifications.¹⁹

Algorithmic pricing—a concept not even mentioned in the 2008 Organisation for Economic Co-operation and Development (OECD) Policy Roundtable on RPM²⁰—is now garnering increased attention from regulators in connection with RPM. In a recent enforcement matter, the U.K.’s Competition and Markets Authority (CMA) recognized that both sellers and distributors can monitor prices with algorithms to help enforce RPM arrangements.²¹ Suppliers can use algorithmic price monitoring to identify deviations from RPM arrangements that have been set implicitly or explicitly, which can lower the cost that suppliers must incur to enforce their RPM arrangements. Distributors can use algorithmic price monitoring to inform supplier if competitors deviate from RPM arrangements and can use algorithmic pricing to match competitors’ prices.²²

Although algorithmic price monitoring has made RPM easier for suppliers to enforce, the effects on competition remain unclear. Currently, there is insufficient empirical evidence to determine whether algorithms are more likely to be used to enforce anticompetitive or procompetitive instances of RPM. However, future disputes involving RPM likely will give the impression that algorithms are being used for anticompetitive purposes. As some have noted, RPM disputes are more likely to reflect instances of RPM that have anticompetitive effects on net.²³ Additionally, the use of algorithmic pricing has increased across retailers. Algorithms do not change the incentives for retailers to report arrangements to regulators or to litigate where the effects are anticompetitive. As a result, any increase in RPM lawsuits that involve algorithmic pricing or algorithmic price monitoring does not necessarily indicate that algorithms are more likely to be associated with anticompetitive uses of RPM.

Regardless of their competitive effects, it is fair to expect that algorithmic pricing and algorithmic price monitoring will make RPM the subject of greater scrutiny going forward.²⁴

¹⁸ See OECD, *Policy Roundtables: Resale Price Maintenance 2008*, DAF/COMP (2008)37 (Sept. 2009), <http://www.oecd.org/daf/competition/43835526.pdf>.

¹⁹ For an overview of procompetitive and anticompetitive theories of RPM, see Alexander MacKay & David Smith, *The Empirical Effects of Minimum Resale Price Maintenance* (Kilts Booth Marketing Series, Paper No. 2-006, 2014), <http://dx.doi.org/10.2139/ssrn.2513533>, at 6-9; Benjamin Klein, *Competitive Resale Price Maintenance in the Absence of Free Riding*, 76 ANTITRUST L.J. 431 (2009).

²⁰ See OECD, *Policy Roundtables: Resale Price Maintenance 2008*, DAF/COMP (2008)37 (Sept. 2009), <http://www.oecd.org/daf/competition/43835526.pdf>.

²¹ In a 2019 action against Casio Electronics, the U.K.’s Competition and Markets Authority (CMA) noted that Casio relied on price email alerts from Price2Spy to monitor changes in reseller prices. It also found that retailers proactively policed each other’s pricing through algorithmic price monitoring software. See CMA, *Decision of the Competition Markets Authority: Online Resale Price Maintenance in the Digital Piano and Digital Keyboard Sector, Case 50565-2* (Aug. 1, 2019), https://assets.publishing.service.gov.uk/media/5d9c539aed915d399eb2160b/non_conf_decision_arrow.pdf, at 36-37; Simon Zekaria, *Casio’s Record UK Fine is Early Evidence of CMA Switching on to Digital Abuses*, MLEX (Aug. 19, 2019), <https://mlexmarketinsight.com/insights-center/editors-picks/area-of-expertise/antitrust/casios-record-uk-fine-is-early-evidence-of-cma-switching-on-to-digital-abuses>.

²² Under both anticompetitive and procompetitive uses of RPM, compliant distributors benefit when their competitors cannot offer lower prices.

²³ RPM cases that are litigated are likely a biased sample of RPM instances that are more likely to have anticompetitive effects on net. Where RPM is permitted and the effects are not clearly procompetitive on net, suppliers are likely to handle enforcement of RPM contracts out of court due to legal risks and because suppliers can unilaterally withhold a product from a distributor. Where RPM is not permitted, distributors are unlikely to bring suit when they benefit from the arrangement (*i.e.*, when there are clear procompetitive benefits of the agreement). See Alexander MacKay & David A. Smith, *Challenges for Empirical Research on RPM*, 50 REV. INDUS. ORG. 209 (2017).

²⁴ For example, in a July 2018 press release discussing fines given to four consumer electronics manufacturers that had imposed RPM on online retailers, the European Commission argued that algorithmic pricing can exacerbate the effects of RPM contracts. Specifically, the Commission stated that because online retailers “use pricing algorithms which automatically adapt retail prices to those of competitors[,] ... the pricing restrictions imposed on low pricing online retailers typically had a broader impact on overall online prices for the respective consumer electronics products.” Press Release, European Commission, *Antitrust: Commission Fines Four Consumer Electronics Manufacturers for Fixing Online Resale Prices* (July 24, 2018), https://ec.europa.eu/commission/presscorner/detail/en/IP_18_4601. The Commission did not appear to take issue with the use

Algorithmic Pricing and Price Discrimination

Price discrimination is a practice whereby firms charge different prices for the same product to disparate customer segments for reasons unrelated to costs. For example, movie theaters discount tickets for seniors, and airlines discount advance-purchase tickets that are more often purchased for vacation travel.²⁵ Algorithmic pricing can facilitate price discrimination by helping firms identify a customer's willingness to pay.²⁶ For example, certain online retailers may use algorithms that price based on an estimate of the customer's physical distance from rival brick-and-mortar stores.

As algorithms become more sophisticated, they may be able to predict consumer preferences with increasing accuracy. If consumer perceptions are subject to common cognitive biases—such as overestimating the frequency of use of a product and thereby the benefits of that product—algorithms that price discriminate based on these perceptions could reduce efficiency.²⁷

In competitive markets where firms have roughly equal access to consumer data, however, consumers could benefit from algorithmic pricing that treats “each consumer [as] a market in its own right.”²⁸ Indeed, price discrimination could improve efficiency by providing lower prices to customers who might not participate in the market otherwise, increasing total surplus. In practice, algorithmic price discrimination that relies on consumer-

specific information can be difficult to implement, as it requires sophisticated programming and substantial computing power that provides consumer-specific prices as quickly as a website loads. Furthermore, as consumers learn that their browser's digital footprint may invite sellers to offer them higher prices than some unknown consumer, they may adopt privacy tools or rely on third-party apps that help disguise customer attributes. Some have noted that, along with the benefits of using algorithms to efficiently price to customers, systemic biases codified in algorithmic pricing could raise questions of fairness.²⁹ For example, biases in the programming of algorithms or in the outcome of such coding may lead to unintended disparate impact.³⁰ However, decisions made by a pricing algorithm are more transparent than those made by humans, as algorithmic pricing strategies can be scrutinized and investigated in artificial environments without resistance from the algorithm. And a well-designed algorithm can help adjust for known biases in human judgment.³¹ Some researchers have already proposed approaches to quantifying disparate impact in pricing algorithms.³² Presumably, resolving biases in a pricing algorithm could be easier to address than resolving human biases.

There can be efficiencies to using algorithms to implement the long-standing practice of price discrimination. Understanding the competitive effects of algorithmic pricing, however, requires

of pricing algorithms or the companies that used or created such software. *Id.* The Commission also did not articulate the market conditions or characteristics that make algorithmic pricing more likely to exacerbate the effects of RPM or whether it is more likely to do so where RPM has anticompetitive effects on net. *Id.*

²⁵ See, e.g., Joanna Stavins, *Price Discrimination in the Airline Market: The Effect of Market Concentration*, 83 REV. ECON. & STAT. 200 (2001).

²⁶ Airlines have long used algorithmic pricing and price discrimination.

²⁷ Oren Bar-Gill, *Algorithmic Price Discrimination When Demand Is a Function of Both Preferences and (Mis)perceptions*, 86 U. CHI. L. REV. 217, 217 (2019), available at <https://chicagounbound.uchicago.edu/uclrev/vol86/iss2/12/>, at p. 217.

²⁸ Axel Gautier, Ashwin Ittoo, & Pieter Cleynenbreugel, *AI Algorithms, Price Discrimination and Collusion: A Technological, Economic and Legal Perspective*, 50 EUR. J. LAW & ECON. 405 (2020).

²⁹ Peter Seele, Claus Dierksmeier, Reto Hofstetter, & Mario D. Schultz, *Mapping the Ethicality of Algorithmic Pricing: A Review of Dynamic and Personalized Pricing* (J. Bus. Ethics Rev. Paper, 2019), <https://link.springer.com/content/pdf/10.1007/s10551-019-04371-w.pdf>.

³⁰ See, e.g., Ziad Obermeyer, Brian Powers, Christine Vogeli, & Sendhil Mullainathan, *Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations*, 366 SCIENCE 447 (2019); Robert Bartlett, Adair Morse, Richard Stanton, & Nancy Wallace, *Consumer-Lending Discrimination in the FinTech Era* (NBER Working Paper No. 25943, 2019), <https://www.nber.org/papers/w25943>.

³¹ See Bo Cowgill & Catherine E. Tucker, *Algorithmic Fairness and Economics* (Colum. Bus. Sch. Res. Paper, 2020), <https://ssrn.com/abstract=3361280>.

³² See, e.g., Akshat Pandey & Aylin Caliskan, *Iterative Effect-Size Bias in Ridehailing: Measuring Social Bias in Dynamic Pricing of 100 Million Rides*, ARXIV (2020), <https://arxiv.org/abs/2006.04599>.

Careful consideration of market outcomes with and without algorithms.

Conclusion

Regulators, policymakers, lawyers, and economists alike are interested in the competitive effects of pricing algorithms. Algorithmic pricing provides many benefits, such as reducing costs of pricing decisions, price monitoring, and incorporating information on variations in supply and demand. Whether pricing algorithms facilitate collusion or lead to reduced consumer welfare remains an open empirical question. Ultimately, the answer to this empirical question will depend critically on the intention and actions of the competitors, the structure of the algorithms, and the net effect on prices, output, and innovation. Although traditional tools of competition policy have been capable of dealing with cases to date involving algorithmic pricing, it remains uncertain whether algorithmic pricing poses new challenges to competition policy.

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