Automated Pricing Algorithms and Collusion: A Brave New World or Old Wine in New Bottles?

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Automated algorithms, which may incorporate analysis from machine learning artificial intelligence (AI), are increasingly used by firms to optimize their pricing decisions. For example, algorithms used by ride-sharing companies such as Uber and Lyft adjust prices of car rides in real time to balance the supply of available drivers and the demand for rides. Dynamic pricing algorithms are also expanding into brick-and-mortar stores, with physical stores like Kohl's and Nebraska Furniture Mart adopting electronic price tags to match the latest offers from online competitors and with firms such as McKinsey and Eversight providing software that enables AI-driven algorithmic pricing at brick-and-mortar retail chains.[1] The use of such automated pricing algorithms in conjunction with big data has the potential to provide significant benefits to consumers by enabling suppliers to become more efficient and swift in responding to market demands.

However, some regulators and industry participants have raised concerns that the adoption of automated pricing algorithms may increase the likelihood of tacit collusion, perhaps even without direction from human decision makers. From an economics perspective, the question can be framed this way: whether (1) automated pricing algorithms represent a brave new world that requires new tools and a paradigm shift in the way we think about collusion, or (2) those antitrust concerns can be appropriately analyzed using principles built up over decades of research into the economics of collusion.

This article examines the features of automated algorithmic pricing that spark concerns about tacit collusion and considers what economic theory can tell us about how increased adoption of automated algorithmic pricing may influence firms' incentives to collude. We find that possible collusion in algorithmic pricing can and should be analyzed using principles of economics that have been refined over decades. Moreover, economic theory teaches that, while the use of automated pricing algorithms may reduce some barriers to collusion, it may also intensify other factors that raise barriers to collusion. Assessing the competitive effects of algorithmic pricing requires careful economic analysis that considers the totality of the market-specific conditions in each case.

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A Brave New World of Automated Collusion?

Some academics, industry participants, and regulators have suggested that an extensive use of automated pricing algorithms may increase the likelihood of collusion. For example, Ariel Ezrachi and Maurice Stucke warn of a future where "as competitors' prices shift online, their algorithms

[1] *See* Spencer Soper, *Amazon Showrooming Forces Stores to Go Digital on Price Displays*, Bloomberg (July 17, 2015), https://www.bloomberg.com/news/articles/2015-07-17/amazon-showrooming-forces-stores-to-go-digital-on-price-displays; Gadi Benmark. Sebastian Klapdor, Mathias Kullmann & Ramji Sundararajan, *How Retailers Can Drive Profitable Growth Through Dynamic Pricing*, McKinsey & Company (Mar. 2017), https://www.mckinsey.com/industries/retail/our-insights/how-retailers-can-drive-profitable-growth-through-dynamic-pricing; Kyle Wiggers, *Eversight Uses AI to Optimize Pricing in Brick-and-Mortar Stores*, VentureBeat (June 25, 2018), https://venturebeat.com/2018/06/25/eversight-uses-ai-to-optimize-pricing-in-brick-and-mortar-stores/.

can assess and adjust prices . . . within milliseconds . . . swiftly match[ing] a rival's discount, thus eliminating its incentive to discount in the first place."[2] A 2017 report from the Organization for Economic Co-operation and Development (OECD) expressed concerns that the use of algorithmic pricing may result in "high price transparency and high-frequency trading that allows companies to react fast and aggressively [which] could make collusive strategies stable" and that "algorithms might enable firms to achieve the same outcomes of traditional hard core cartels through tacit collusion."[3]

These concerns were echoed in a recent article co-authored by then-FTC Commissioner Terrell McSweeny, which discusses a "possibility . . . that algorithms may facilitate tacit collusion between competitors" and cites a finding by Bruno Salcedo "that under certain conditions, tacit collusion between firms employing pricing algorithms is . . . inevitable."[4] Participants at the recent 2018 FTC hearings on "Competition and Consumer Protection in the 21st Century" discussed similar concerns regarding the likelihood of such algorithmic collusion.[5]

The concerns raised over potential collusion using pricing algorithms can be grouped into three scenarios: (1) the use of automated algorithms to implement explicit collusive pricing agreements between competitors; (2) "hub-and-spoke" scenarios where competitors (spokes) use a common third-party pricing algorithm (hub), which may lead to coordinated pricing; and (3) unilateral use of self-learning autonomous pricing algorithms by competitors that may nonetheless lead to supracompetitive prices through conscious parallelism or tacit collusion.[6] The economic analyses presented in this article apply to the economic principles and market forces that affect the likelihood of collusion arising from all three scenarios.

The first and second scenarios described above both require explicit agreements on the part of human decision makers—these are essentially the smoke-filled room agreements of the digital era. The first online marketplace antitrust prosecution by the DOJ is such an example of an agreement implemented using computer algorithms.[7] However, it has always been possible for competitors to coordinate—either directly, or through human third-party "hub" pricing schemes, such as a common third-party consulting agency, without the use of any automated algorithms. In the words of former FTC Commissioner Maureen Ohlhausen, "If it isn't ok for a guy named Bob to do it, then it probably isn't ok for an algorithm to do it either."[8]

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[2] Ariel Ezrachi & Maurice E. Stucke, Virtual Competition: The Promise and Perils of the Algorithm-Driven Economy 62 (2016).

[3] OECD, Algorithms and Collusion: Competition Policy in the Digital Age 51 (Sept. 14, 2017), http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm.

[4] Terrell McSweeny & Brian O'Dea, *The Implications of Algorithmic Pricing for Coordinated Effects Analysis and Price Discrimination Markets in Antitrust Enforcement*, Antitrust, Fall 2017, at 75, 76.

[5] Maurice Stucke & Joseph Harrington, Remarks Before the FTC Hearings on Competition and Consumer Protection in the 21st Century (Nov. 14, 2018), https://www.ftc.gov/system/files/documents/public_events/1418693/ftc_hearings_session_7_transcript_day_2_11-14-18.pdf.

[6] *See, e.g.*, Ezrachi and Stucke's discussion of the "Computer as Messenger," "Hub and Spoke," "Predictable Agent," and "Digital Eye" scenarios of collusion involving automated pricing algorithms. Both the "Predictable Agent," and "Digital Eye" discussions envision the possibility of tacit collusion via automated algorithms without explicit agreements between human decision makers. Arial Ezrachi & Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition*, 2017 Univ. Ill. L. Rev. 1775, 1784–1796 (2017).

[7] In *United States v. Topkins*, David Topkins and his co-conspirators agreed to fix the prices of posters sold through Amazon Marketplace and implemented their agreements by adopting specific pricing algorithms. *See* Press Release, U.S. Dep't of Justice, 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; Plea Agreement at 4, United States v. Topkins, No. CR 15-00201 WHO (N.D. Cal. 2015), https://www.justice.gov/atr/case-document/file/628891/download.

The economics of these types of collusion scenarios do not change when algorithms are involved, and as such, the fundamental economic problem of coordination applies to potential collusive schemes, whether it be through automated pricing algorithms or human agreement. These scenarios of collusion still fundamentally depend on human agreement.

The third scenario of potential collusion envisions situations in which, even without explicit agreements among competitors, unilateral use of automated pricing algorithms by competitors may lead to supracompetitive prices through conscious parallelism or tacit collusion. As a preliminary matter, as acknowledged by Ezrachi and Stucke, "[a]lgorithmic tacit collusion will not affect every (or even most) markets."[9] In their discussions of algorithmic tacit collusion scenarios, Ezrachi and Stucke focus on concentrated markets where credible deterrent mechanisms exist for enforcing collusion and barriers to entry are high[10]—market settings that have been identified in classical economic studies to have elevated risks of collusion.

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Within the context of such market settings, the discussion often centers around two features of algorithmic pricing: (1) greater transparency of prices as sellers post their prices online and more market data becomes accessible, which purportedly makes it easier for collusive firms to detect those that cheat and undercut the collusive price; and (2) the ability to rapidly react to competitors' pricing changes, which purportedly enables collusive firms to rapidly punish cheating firms that undercut the collusive price (by matching or further undercutting the prices of the cheating firm). These two features correspond to factors that are well understood within the economic literature to affect the sustainability of collusion in general—information availability and frequency of interaction between competitors. As such, how changes in these factors would influence incentives to collude and the sustainability of collusive arrangements are well within the scope of economic models of competition developed over the decades. Just as the increased calculation speeds by computers do not change the fundamental laws of mathematics, the increased velocity of decision making by automated algorithms does not change the fundamental forces of competition.

Tacit collusion between AI pricing algorithms remains within the realm of hypothetical predictions. There has been no empirical evidence demonstrating collusion between AI algorithms in real-world markets—a fact the Canadian Competition Bureau noted when it stated that "suggesting a fundamental shift in cartel law enforcement" to address such hypothetical concerns would be "premature."[11] Maureen Ohlhausen similarly stated that "[f]rom an antitrust perspective, the expanding use of algorithms raises familiar issues that are well within the existing canon" and that, while the "enforcement agencies should remain vigilant" about pricing algorithms, she is "not yet afraid of the things that go beep in the night."[12]

The absence of evidence from empirical studies on real world market settings does not appear to be driven by a lack of interest from economists. On the contrary, the economic implications of

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[8] Maureen K. Ohlhausen, Should We Fear the Things That Go Beep in The Night? Some Initial Thoughts on the Intersection of Antitrust Law and Algorithmic Pricing, Remarks from the Concurrences Antitrust in the Financial Sector Conf. 10 (May 23, 2017) [hereinafter Ohlhausen 2017 Speech], https://www.ftc.gov/system/files/documents/public_statements/1220893/ohlhausen_-_concurrences_5-23-17.pdf.

[9] Ariel Ezrachi & Maurice E. Stucke, *Algorithm Collusion: Problems and Counter-Measures*, OECD Roundtable on Algorithms and Collusion 3 (May 31, 2017) [hereinafter Ezrachi & Stucke, OECD Roundtable], http://www.oecd.org/daf/competition/algorithms-and-collusion.htm.

[10] *See, e.g.*, *id.* at 3–4.

[11] Competition Bureau Canada, Big Data and Innovation: Key Themes for Competition Policy in Canada 11 (Feb. 19, 2018), http://www.competitionbureau.gc.ca/eic/site/cb-bc.nsf/vwapj/CB-Report-BigData-Eng.pdf/$file/CB-Report-BigData-Eng.pdf.

[12] Ohlhausen 2017 Speech, *supra* note 8, at 11.

AI are the subject of intense interest from professional economists, as can be seen through the wide range of research presented at the annual "Economics of AI" conference hosted by the National Bureau of Economic Research, including studies on the effects of AI on competition between firms.[13] However, given the absence of empirical evidence from real-world market settings, the research on tacit collusion between AI pricing algorithms remains a theoretical inquiry with no demonstrated real-world evidence.[14]

Economic models are capable of assessing the effects of automated algorithms on incentives to collude, whether tacitly or explicitly. This is because automated algorithmic pricing does not change the fundamental economic principles that govern competition and incentives to collude. The effects of automated algorithmic pricing likely will differ case by case, based on the specific algorithms used and the specific market conditions. To properly assess such effects, we must apply economic principles to the facts of each case and holistically examine the ways in which automated pricing algorithms may change how firms interact and their incentives to collude.

As we discuss below, increases in information availability and frequency of interaction between competitors are not the only ways in which automated pricing algorithms can change economic incentives to collude. On the contrary, the same technology that brings about increases in information availability and frequency of interaction between competitors may also engender factors that hinder collusion.

Rational Decision Makers Are Not New in Economics

While automated algorithms and AI, hailed by some as a key driver of the "Fourth Industrial Revolution,"[15] are undeniably transforming the economy, the economic principles that underlie demand, supply, and competition have not changed. Decisions by competitors to collude, whether through explicit smoke-filled-room agreements or through interactions of automated algorithms, will continue to be driven by the economic incentives facing the decision makers.

Classical economic models of competition consider decision making by rational market participants. Strategic interactions and price competition between those market participants can be thought of as "games" defined by what information (e.g., competitors' prices and pricing histories) each firm has access to, the choice of actions (e.g., pricing) available to each firm, and profits and sales each firm would earn given their pricing choices.[16] Given these factors, a rational agent chooses the strategy that maximizes its profits.

This objective to maximize profits is the same whether prices are set by humans or automated pricing algorithms. Some commentators have opined that classical economic models may not be applicable for assessing algorithmic pricing based on arguments in the vein of "[a]ll of the economic models are based on human incentives and what we think humans rationally will do. It's

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[13] *See* National Bureau of Economic Research, The Economics of Artificial Intelligence: An Agenda (Sept. 13, 2017), https://papers.nber.org/books/agra-1.

[14] *See, e.g.*, Emilio Calvano et al., *Algorithmic Pricing: What Implications for Competition Policy?* (June 27, 2018), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3209781.

[15] *See, e.g.*, Klaus Schwab, *The Fourth Industrial Revolution: What It Means, How to Respond*, World Economic Forum (Jan. 14, 2016), https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond.

[16] This is the game-theory framework for analyzing strategic interactions, first developed by Nobel Laureate John Nash. Within the game-theory framework, games of strategic interaction are defined by the list of players participating in the game, the information and actions available to each player at each decision point, and the payoffs for each outcome of the game. *See, e.g.*, Martin J. Osborne, An Introduction to Game Theory 13–14 (2004).

entirely possible that not all of that learning is necessarily applicable in some of these markets."[17] However, such arguments are based on misconceptions of what is rational decision making and/or the underlying assumptions of classical economic models. Decision making, as the automated pricing algorithms are programmed to carry out, is no different from the type of decision making that is governed by mathematical logic with the goal of maximizing profits for the firm. These are exactly the scenarios modeled in classical economics.

Given the firms' chosen pricing strategies, profits are driven by demand and costs facing each firm—market forces that govern both human and algorithmic pricing competition. Therefore, automated pricing algorithms do not change any of the ground rules of price competition between firms. As discussed above, commentators have suggested that automated pricing algorithms may change the information available to decision makers in these games and the speed of the game[18] because some automated algorithms can react to market developments in a matter of milliseconds, increasing the frequency of interactions between firms. In addition, commentators have argued that the same technology that gives rise to the use of automated pricing algorithms can increase the amount of information each firm observes and relies upon in its pricing decisions, reducing information asymmetry across firms.[19]

There is an extensive economics literature that examines strategic pricing interactions between rational agents with varying degrees of information asymmetry and interaction time.[20] Below, we discuss what we can learn from the economics literature about how these changes brought about by automated pricing algorithms may influence incentives for collusion.

Back to Basics: What Economic Theory Teaches About Collusion

Classic economic theory of collusion teaches that firms need to resolve a series of problems to sustain collusion. First, firms need to reach a collusive arrangement. That is, each firm needs to find it in its unilateral best interest to adopt the cooperative (i.e., collusive) strategy rather than a competitive one. This problem of finding a collusive strategy that all firms are willing to adopt is common to overt and tacit collusion. Second, for collusion to be sustained, firms need to find it in their unilateral best interest to follow through with the collusive strategy without deviation. That is, the economic benefit from sticking with the collusive strategy needs to exceed the economic benefit from unilaterally deviating from it. A collusive arrangement that raises the industry prices above competitive levels engenders economic incentives for individual firms to undercut their competitors' prices to capture a larger share of the market (i.e., to cheat on the collusive arrangement). Mechanisms to detect and punish such behavior are necessary to discourage cheating on the collusive arrangement and sustain collusion. Below, we discuss these and other economic fac-

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[17] David J. Lynch, *Policing the Digital Cartels*, Fin. Times, Jan. 8, 2017, https://www.ft.com/content/9de9fb80-cd23-11e6-864f-20dcb35cede2 (statement of Terrell McSweeny, Comm'r, Fed. Trade Comm'n).

[18] *See, e.g.*, Ezrachi & Stucke, OECD Roundtable, *supra* note 9, at 3–4; Michal S. Gal, *Algorithmic-Facilitated Coordination: Market and Legal Solutions*, Antitrust Chron. 24 (Apr. 2017), at 3; Salil K. Mehra, *Antitrust and the Robo-Seller: Competition in the Time of Algorithms*, 100 Minn. L. Rev. 1323, 1347–49 (2016).

[19] *See* sources cited, *supra* note 18.

[20] The classic prisoner's dilemma assumes that there is no information asymmetry between the firms—both firms know the profit that each firm would make under different market outcomes. Edward Green and Robert Porter developed an economic model in which a firm's output is private information. Because firms do not observe others' output level, they cannot distinguish what might have caused a decline in sales—a deviation by another firm from the corporative strategy (i.e., an expansion in output) or a low demand shock. Edward J. Green & Robert H. Porter, *Noncooperative Collusion Under Imperfect Price Information*, 52 Econometrica 89–90 (1984).

tors that can hinder or facilitate collusion and whether those factors change with the use of automated pricing algorithms.[21]

Ability to Reach a Collusive Arrangement. Economic incentives to collude exist when the total economic profits from collusion (i.e., when firms make joint decisions to maximize industry profit) exceed the total economic profits from competition. Consider two markets that are identical except that one market has only one supplier (a monopoly) and the other has two (a duopoly). It is well established in economics that the profit made by the monopolist exceeds the combined profits of the two firms in the duopoly. Those two firms therefore have an economic incentive to act jointly to behave like a monopoly and split the monopoly profit.

Having economic incentives to collude does not necessarily engender a collusive outcome. To sustain collusion, the colluding firms must find a way to split the gains from collusion such that all participants in the collusive scheme are made better off. Otherwise, firms would find it in their unilateral best interests to adopt the competitive strategy rather than to cooperate in the collusive scheme. Therefore, a mechanism to split the gains from collusion is necessary for sustaining collusion, whether it be overt or tacit. The use of automated pricing algorithms does not eliminate the need for such profit-splitting mechanisms to reach a collusive arrangement.

[U]se of automated pricing algorithms does not alleviate coordination issues that must be resolved to implement either overt or tacit collusion.

Several market conditions can affect the likelihood of finding a way to split the gains from collusion. In a simplified example in which all firms are identical (i.e., firms make the same product and face the same cost), there may be relatively straightforward ways to divide the gains from collusion. For example, some market allocation arrangements may ensure firms can equally distribute gains from collusion.

However, finding a way to split the gain from collusion may be harder when firms are asymmetric. Firms can differ in many aspects. For example, asymmetry in costs can arise when firms have different levels of productivity. A well-managed firm may be more productive, and thereby more efficient, than its competitors.

Cost asymmetry may complicate the allocation of gains from collusion. Take, for example, a scenario in which there are two firms, one with a higher cost of production than the other firm. A collusive scheme may be for the firm with the lower cost to supply the entire market and then share its profit with the firm with the higher cost. Reaching an agreement on how the gains from such an arrangement should be split may involve side payments from one firm to the other.[22] Setting aside the legal implications of such payments, a series of other economic problems need to be resolved before both firms would agree to such a collusive arrangement. For example, how would such a transfer take place? How will the firms solve the commitment issue—i.e., can the firm with the higher cost be certain that the firm that supplies the entire market will share the profit rather than keep the profit to itself?

The use of automated pricing algorithms does not alleviate coordination issues that must be resolved to implement either overt or tacit collusion. For example, it remains an open question the extent to which, if at all, the use of automated algorithms can solve the allocation issue in the presence of cost asymmetries. In the first instance, the use of automated pricing algorithms is unlikely to resolve cost asymmetries across firms. Second, economic literature provides no predictions

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[21] The discussion below is not meant to provide an exhaustive list of such economic factors. For a more detailed discussion of the economic theories of collusion, see, e.g., Alexis Jacquemin & Margaret E. Slade, *Cartels, Collusion, and Horizontal Merger*, 1 HANDBOOK OF INDUSTRIAL ORGANIZATION 417–23 (Richard Schmalensee & Robert Willig eds., 1989).

[22] *Id.* at 418.

on how automated algorithms can facilitate finding ways to divide gains from collusion in cases when no such agreements are reached by humans.

Incentives to Cheat. As firms enter into a collusive arrangement, they have incentives to cheat by deviating from the collusive arrangement and undercutting competitors to obtain larger market shares. Such unilateral deviations from the collusive strategy can result in substantial increases in profit made by that firm while the other firms continue to implement the collusive strategy.

Economics teaches that a key step to assess the sustainability of collusion is to examine the market conditions that can affect firms' incentives to cheat on the collusive prices and/or quantities. A firm's incentive to cheat depends on how much more in sales it can obtain by offering a lower price—a concept known as demand elasticity. The higher the demand elasticity, the more sales the firm can obtain with a reduction in price, and hence increasing the incentive to cheat.

A firm's cost structure can also affect its incentive to cheat and undercut collusive prices. For a firm with high fixed costs, restricting output as part of a collusive arrangement may not only result in excess production capacity but also limit the firm's ability to recover its fixed cost. Therefore, compared to firms with low fixed costs, firms with high fixed costs may have more economic incentives to cheat on collusive agreements by expanding output.

It remains an open question whether and how the use of automated pricing algorithms affects the demand and cost conditions mentioned above. For example, the rise of online retail and automated comparison-shopping services such as Google Shopping and Kayak may make consumers more price sensitive, thereby increasing the demand elasticities and economic incentives for firms to gain sales by undercutting collusive prices. On the other hand, the rise of e-commerce may also increase the level of product differentiation, making the products more tailored to specific groups of consumers, resulting in more inelastic demand for those products.

Mechanisms to Deter Cheating on Collusive Arrangements. Because firms have incentives to cheat on collusive arrangements, mechanisms to deter cheating must exist to sustain collusion. Such deterrence can take various forms, but the basic intuition is the same—the prospect that cheating would be met with punishment severe enough to make the costs of cheating outweigh its benefits.

The effectiveness of a deterrence mechanism depends on several factors: (1) whether cheating can be easily detected; (2) the severity of the expected punishment; and (3) the credibility of the prospect of punishment. Below we discuss market conditions that can affect each of those factors.

Whether cheating can be easily detected by co-conspirators depends on the existence and extent of information asymmetry. In a world in which all information is observed by all firms, detection is straightforward—cheating can be observed as demand, price, cost, and even a firm's pricing strategy are public information in a world with full information. However, firms often have private information on pricing and costs. In the presence of private information, detection becomes less straightforward.

While, as suggested by some commentators, the use of automated pricing algorithms may alleviate information asymmetry,[23] it may also contribute to information asymmetry, which, as discussed above, hinders collusion. Companies may develop their own automated pricing algorithms or use different suppliers to manage their automated pricing algorithms. It therefore becomes

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[23] *See, e.g.*, OECD, Algorithms and Collusion: Competition Policy in the Digital Age 51 (2017), http://www.oecd.org/daf/competition/Algorithms-and-colllusion-competition-policy-in-the-digital-age.pdf.

unclear what information each algorithm would consider when making pricing decisions. Put differently, when one algorithm considers a set of factors and a second algorithm does not, it is as if those factors are private information to the first algorithm. In this way, the use of automated pricing algorithms therefore may increase information asymmetry.[24]

A deterrence mechanism's effectiveness also depends on the time needed to implement punishment after cheating is detected. To understand this, consider a scenario in which, when a firm cheats on the collusive price, all other firms in the collusive cartel will punish the cheating firm by pricing their competing products at low prices going forward. Hence, the cheating firm would make higher profits while the cheating remains undetected, but after cheating is detected, it will make lower profits than if it had not cheated. This is because competition from the other firms' low prices would reduce the cheating firm's profits. The punishment is therefore the decline in future profits. The firm would cheat only if the temporary increase in profits from cheating is greater than the decline in future profits. The longer it takes to detect cheating, the larger the gain from cheating.

The frequency with which competitors can react to each other's price changes is a factor that affects the time lags between cheating, detection, and punishment. As interactions become more frequent, the time lags between interactions shorten and the possibility of a punishment becomes more immediate, increasing the deterrence effect of punishment threats. All else being equal, if the time lags between cheating, detection, and punishment are reduced, the costs of cheating on a collusive agreement would increase.

Commentators have raised the concern that automated algorithms would decrease these time lags and make collusion more likely. However, the rapid reaction speeds enabled by automated pricing algorithms and online retail platforms may be somewhat of a double-edged sword for would-be collusive firms. While the increased reaction speeds may allow for faster detection and punishment of cheating firms, online retail platforms and algorithmic pricing may also change the market landscape in other ways that make collusion more difficult. For example, online retail platforms such as Amazon and Alibaba enable sellers from around the globe to compete for local sales,[25] and the rapid-reaction pricing may sharpen competition and spark price wars that would make collusion difficult.[26]

Detection and reaction time lags are not the only factors that influence the ability of conspiring firms to enforce collusion. The severity of a punishment may be bound by other factors such as capacity constraints. In industries where increasing production capacity in the short term is difficult, conspiring firms may not be able to expand output sufficiently to deter cheating. The use of rapid-reaction automated pricing algorithms would not make collusion any easier in such circumstances.

Entry. Another important factor is the threat of entry by additional competitors when incumbent firms collude. As collusion raises price, it naturally attracts new firms to enter the market. Economics teaches us that in the absence of entry barriers, new competitors would continue to enter the market until the excess profit from collusion dissipates through increased competition. When entry barriers are present, it would be economically rational for new competitors to enter as long

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[24] *See, e.g.*, Thore Graepel et al., *Multi-Agent Reinforcement Learning in Sequential Social Dilemmas*, PROCEEDINGS OF THE 16TH INTERNATIONAL CONFERENCE ON AUTONOMOUS AGENTS AND MULTIAGENT SYSTEMS (2017).

[25] *See, e.g.*, John Herrman, *The Online Marketplace That's a Portal to the Future of Capitalism*, N.Y. TIMES MAGAZINE, May 3, 2017, https://www.nytimes.com/2017/05/03/magazine/the-online-marketplace-thats-a-portal-to-the-future-of-capitalism.html.

[26] *See, e.g.*, Stephanie Clifford, *Retail Frenzy: Prices on the Web Change Hourly*, N.Y. TIMES, Nov. 30, 2012, https://www.nytimes.com/2012/12/01/business/online-retailers-rush-to-adjust-prices-in-real-time.html.

as profits under the collusion-inflated prices exceed the costs of entry. Therefore, entry by competitors would still restrain the ability of incumbents to raise prices through collusion. The growth of online commerce that goes hand-in-hand with adoption of automated pricing algorithms has led to the creation of online marketplace platforms such as Amazon, eBay, and Google Shopping that arguably lowers the barriers to entry for online retail. To the extent that such platforms are lowering the barriers to entry, they are sharpening the threats of competitive entry, which raises the difficulty of sustaining collusion.

Conclusion

The economics behind antitrust cases involving collusion, by its nature, is complex and nuanced. Adding automated pricing algorithms to the mix only increases the complexity. As such, it should be no surprise that there is no simple "yes" or "no" answer to the question of whether the use of automated algorithms will increase the likelihood of collusion. However, while the strategic games of competitive pricing may now be played at a faster tempo by automated algorithms, the fundamental rules of the game—governed by classical economic principles of supply, demand, and profit maximization—remain the same. Collusion, whether between human conspirators or among automated pricing algorithms, can and should be analyzed using the economic theory that has been honed and refined over the decades.

Applying economic theory to the impact of automated pricing algorithms on market conditions, we find that while the use of automated pricing algorithms may reduce some factors that hinder collusion (e.g., the time it would take for colluding firms to react to cheating), it may also intensify other factors that hinder collusion (e.g., reducing marginal costs and increasing incentives to undercut collusive prices). Assessment of collusion and its economic effects has always required, and always will require careful economic analysis that is informed by rigorous economic theory and considers the totality of the market-specific conditions in each case. ●