Stanford Computational Antitrust

ARTICLE

Antitrust by Algorithm

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Abstract. Technological innovation is changing private markets around the world. New advances in digital technology have created new opportunities for subtle and evasive forms of anticompetitive behavior by private firms. But some of these same technological advances could also help antitrust regulators improve their performance in detecting and responding to unlawful private conduct. We foresee that the growing digital complexity of the marketplace will necessitate that antitrust authorities increasingly rely on machine-learning algorithms to oversee market behavior. In making this transition, authorities will need to meet several key institutional challenges—building organizational capacity, avoiding legal pitfalls, and establishing public trust—to ensure successful implementation of antitrust by algorithm.

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Introduction

Markets are changing around the world. Technological innovation produces a steady stream of new products and services that are disrupting old patterns of economic activity and delivering new value to consumers. At the same time, many of these technologies are also creating new opportunities for rent-seeking behavior by firms. With the rapid pace of innovation, the rise of a small number of big technology firms, and the creation of new ways for companies to collude and evade regulators, the nature of antitrust law and its enforcement will also surely change in the years ahead. Rapid changes in the marketplace bring with them increases in public clamoring and calls for legislative action to rein in big tech firms. These developments also present regulators with new reasons to explore using technological innovations to enhance their own performance in overseeing private market activity.

We cannot forecast exactly what direction the substance of antitrust law will take in the years to come, nor do we take any normative position here on what that substantive direction should be. But we do foresee a shift in antitrust regulators' own use of technology, and we articulate here why antitrust regulators can and should do more to expand their reliance on artificial intelligence (AI) tools to undertake their work.[1] Simply put, we argue that to keep pace with the changing technologically advanced market landscape, antitrust authorities need to enhance their internal capacities both to monitor and analyze markets with speed and accuracy and to identify potential regulatory violations in need of investigatory scrutiny.[2] In the years ahead, antitrust regulators will increasingly turn to what we might call antitrust by algorithm.

We begin in Part I by highlighting how digital technologies, including advances in the use of sophisticated algorithms, have created new opportunities for subtle and evasive forms of anticompetitive behavior by private firms. In Part II, we show how the growing digital complexity of the private marketplace will lead antitrust regulators to rely on many of the same kinds of technologies as private firms do—but instead to advance regulatory purposes, such as detecting anticompetitive behavior and allocating limited enforcement resources. We conclude in Part III that successfully pursuing antitrust by algorithm will require that antitrust regulators confront key institutional challenges in the years ahead, building up their technological and human capital to ensure that they use algorithmic tools effectively in ways that avoid legal vulnerabilities and that ensure public trust and confidence in these tools.

I. Antitrust in an Algorithmic Marketplace

For many decades after the enactment of major antitrust laws in the United States and other major economies, it appeared that regulatory organizations could

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[1] Thibault Schrepel, *Computational Antitrust: An Introduction and Research Agenda*, 1 STAN. J. COMPUTATIONAL ANTITRUST 1 (2021).

[2] A similar argument, but for regulators more generally, can be found in Cary Coglianese, *Optimizing Regulation for the Optimizing Economy*, 4 J. PUB. AFFS. 1 (2018).

oversee the pace of change in the economic marketplace if they simply hired more staff members. Indeed, the most well-regarded antitrust authorities around the world also tend to be the largest.[3]

But in recent years, the nature and pace of change in marketplaces around the world has dramatically shifted to a point where simply hiring more experts may not be enough. Markets have transformed along many dimensions. E-commerce, for example, has become a mainstay within the retail marketplace. Firms have increasingly adopted automated systems to set prices and track business transactions. Market conduct is progressively complex and rapidly changing, and markets have become increasingly more networked and collaborative.[4]

Although antitrust officials have long sought to rely on careful, sophisticated analysis of competition and consumer welfare, now they must seek to fulfill their responsibilities in the face of firm behavior that can fluctuate rapidly and subtly through algorithms, such as with the use of finely differentiated pricing, digital transactions, and new forms of industrial organization.[5]

In this new marketplace emerging around the world, firms in the private sector are conducting a greater number of transactions with more complex structures. An upwards global trend has arisen in the number of mergers and acquisitions across an array of sectors, including pharmaceuticals, media and entertainment, and digital services.[6] Firms, universities, and startups are all entering more technology transfer agreements.[7]

In addition, studies report an increase in deal complexity as firms hunt for ways to create value in a crowded market.[8] Agreements now often involve carve-outs,

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[3] As the authors of a widely known ranking system of antitrust regulators around the world have acknowledged, "the bigger a government's competition budget, the better the enforcement agency gets." GLOB. COMPETITION REV., RATING ENFORCEMENT 2015 (June 18, 2015). *See also* FED. TRADE COMM'N, CONGRESSIONAL BUDGET JUSTIFICATION FISCAL YEAR 2022, at 49 (May 28, 2021), https://www.ftc.gov/system/files/documents/reports/fy-2022-congressional-budget-justification/fy22cbj.pdf (the Federal Trade Commission in the United States has about 600 personnel devoted to antitrust matters); U.S. DEP'T OF JUST., CONGRESSIONAL SUBMISSION FY 2022 PERFORMANCE BUDGET 54 (2021), https://www.justice.gov/jmd/page/file/1398291/download (the U.S. Department of Justice's Antitrust Division comprises about 750 staff members); U.S. DEP'T OF JUST., CONG. SUBMISSION FY 2022 PERFORMANCE BUDGET 54 (2021), EUR. COMM'N, H.R. KEY FIGURES 1 (2021), https://ec.europa.eu/info/sites/default/files/european-commission-hr_key_figures_2021_en.pdf (the European Commission's Directorate-General for Competition has about 850 personnel).

[4] Herbert Hovenkamp, *Monopolizing and the Sherman Act* (Univ. of Pa. Carey L. Sch. Inst. Law Econ., Rsch. Paper No. 22-02, 2022), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3963245.

[5] These changes in the marketplace would only seem to reinforce the need for sound analysis to fulfill what Herbert Hovenkamp calls "the first rule of rational antitrust policy: figure out who is getting hurt, and how." Herbert Hovenkamp, *The Looming Crisis in Antitrust Economics*, 101 B.U. L. REV. 489, 544 (2021).

[6] Jennifer Rudden, *Number of Merger and Acquisition (M&A) Transactions Worldwide From 1985* to *2021*, STATISTA (Jan. 11, 2022), https://www.statista.com/statistics/267368/number-of-mergers-and-acquisitions-worldwide-since-2005/; Anne Sraders, *M&A Activity Has Already Blown Past the $2 Trillion Mark in a Record-Breaking 2021*, FORTUNE (June 2, 2021), https://fortune.com/2021/06/02/mergers-acquisitions-2021-m-and-a-record-year-spacs/; Orla McCaffrey, *Bank Mergers are on Track to Hit Their Highest Level Since the Financial Crisis*, WALL ST. J. (Sept. 28, 2021), https://www.wsj.com/articles/bank-mergers-are-on-track-to-hit-their-highest-level-since-the-financial-crisis-11632793461.

[7] Dipanjan Nag, Antara Gupta & Alex Turo, *The Evolution of University Technology Transfer: By the Numbers*, IPWATCHDOG (Apr. 7, 2020), https://www.ipwatchdog.com/2020/04/07/evolution-university-technology-transfer/id=120451/.

[8] Michael Knott, *Increasingly Complex M&A in the Technology Sector Puts the Spotlight on Effective Due Diligence to Drive Success*, FINANCIER WORLDWIDE MAG., NO. 138 (June 2014), https://www.financier

scale deals, and capability-driven investments, such as technology firms' increased acquisition of cloud-based, mobile, online, and big data technologies.[9] And the day-to-day operation of these firms often relies heavily on data processing, including real-time processing of marketplace factors, automated tracking of supply chains, and collection of massive amounts of data on consumer preferences. Overall, in an economy increasingly driven by data analysis, access to and control over data correspondingly becomes an increasing potential source of market power.[10]

One example of the changing landscape that has potential antitrust implications can be found with the growing reliance on firms' dynamic pricing algorithms. Dynamic pricing refers to a set of pricing strategies aimed at increasing profits by adjusting the set price according to changing variables in supply and demand.[11] When a product has limited capacity and an expiration date, technology now allows a firm, with relative ease, to make larger swings in prices while still being assured of the sale.[12]

Dynamic pricing strategies were introduced by American Airlines in the 1980s and depended upon the company's internal management system that tracked route demand, number of seats, and other factors.[13] These strategies reportedly yielded American Airlines an extra $500 million per year.[14] They also offered the potential to yield significant gains in consumer welfare. In the context of airline prices, evidence indicates that consumers benefit overall when leisure travelers who make reservations in advance receive lower prices than business travelers who make last-minute reservations.[15]

Although welfare-enhancing gains may not always be realized in every industry, the advancement of e-commerce and digital technology does mean that a wider array of firms can use dynamic pricing strategies in real time.[16] Moreover, perfect price discrimination, which was long viewed as impossible, is now increasingly possible to approximate.[17] In the past, traditional retailers were often constrained by lack of data on supply and demand, as well as simple physical limitations associated with the need for manually relabeling prices on products. But

worldwide.com/increasingly-complex-ma-in-the-technology-sector-puts-the-spotlight-on-effective-due-diligence#.Yd-rXRPMI-Q.

[9] *Id.*

[10] *See* Cristian Santesteban & Shayne Longpre, *How Big Data Confers Market Power to Big Tech: Leveraging the Perspective of Data Science*, 65 ANTITRUST BULL. 459 (2020).

[11] *See* Kaveh Waddell, *The Death of Prices*, AXIOS (Apr. 30, 2019), https://www.axios.com/future-of-retail-amazon-surge-pricing-brick-and-mortar-b6a5f9fe-130f-4601-b96f-a3dc7a69b54e.html (with dynamic pricing systems, "prices that are constantly changing, either by time of day or by individual or by demographic type"); *see also* R. Preston McAfee & Vera te Velde, *Dynamic Pricing in the Airline Industry*, ECON. & INFO. SYS. 527 (Terrence Hendershott ed., 2007), https://mcafee.cc/Papers/PDF/DynamicPriceDiscrimination.pdf.

[12] *Id.*

[13] *Id.*

[14] *Id.*

[15] *See* Kevin R. Williams, *The Welfare Effects of Dynamic Pricing: Evidence from Airline Markets* (Nat'l Bureau of Econ. Rsch., Working Paper No. 28989, 2021).

[16] *See* Le Chen, Alan Mislove & Christo Wilson, *An Empirical Analysis of Algorithmic Pricing on Amazon Marketplace*, PROC. OF THE 25TH INT'L CONF. ON WORLD WIDE WEB (2016), http://www.ccs.neu.edu/home/amislove/publications/Amazon-WWW.pdf.

[17] *See* ORG. FOR ECON. COOP. AND DEV., PRICE DISCRIMINATION, DAF/COMP(2016)15 (Oct. 13, 2016), https://one.oecd.org/document/DAF/COMP(2016)15/en/pdf; Axel Gautier, Ashwin Ittoo & Pieter Van Cleynenbreugel, *AI Algorithms, Price Discrimination and Collusion: A Technological, Economic and Legal Perspective*, 50 EUR. J.L. & ECON. 405 (2020).

today, e-commerce retailers can easily gather data on competitors' prices as well as other variables and then effortlessly modify prices of their products numerous times per day.[18] One study found that the price of products sold by firms using dynamic pricing algorithms fluctuated ten times more than human-priced products, and that firms using dynamic pricing algorithms accounted for one-third of the best-selling products sold by third parties on Amazon.[19]

Dynamic pricing algorithms extend beyond e-commerce retailers. Uber employs a similar price-surging algorithm to set the price of a rideshare according to real-time factors such as available drivers and demand for rides.[20] In times of bad weather or at rush hour, for instance, ride fares will be subject to a fare multiplier. Uber defends the practice as merely adjusting for supply and demand to prevent long wait times and promote ride completion rates.[21] But even if an ordinary auction market would clear the same way—that is, increase price as buyers increased—the use of an algorithm allows for real-time, rapid, and perfect price discrimination. And even if algorithmic systems can adjust prices for legitimate reasons, they also allow new possibilities for anticompetitive behavior.

In fact, Uber has already been sued for alleged antitrust violations related to its use of algorithms.[22] In 2015, Uber was charged with allegations that its price-surging algorithm created an anticompetitive conspiracy between Uber and its drivers because each driver had expressly agreed with Uber to charge certain fares "with the clear understanding that all other Uber drivers are agreeing to charge the same fares."[23] With advancements in the sophistication and reach of smartphone technology and ridesharing applications, Uber has been able to coordinate agreements between "hundreds of thousands of drivers in far-flung locations" despite the fact that none of the drivers had communicated directly with one another.[24] Although the arbitrator in the lawsuit ultimately decided in favor of Uber due to a lack of evidence of agreements among drivers to work for the same price,[25] what the district court judge wrote in that case aptly describes the challenge for antitrust today and into the future: "The advancement of technological means for the orchestration of large-scale price-fixing conspiracies need not leave antitrust law behind."[26]

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[18] *See* Chen, Mislove & Wilson, *supra* note 16, at 1, 9; Xuesong Zhao, *Big Data and Price Discrimination*, 2020 IEEE 5TH INT'L CONF. ON CLOUD COMPUTING & BIG DATA ANALYTICS 471 (May 19, 2020), https://ieeexplore-ieee-org.proxy.library.upenn.edu/document/9095721.

[19] *Id. See also* Matthew D. Ridings & Mark Butscha, *Algorithms and Antitrust Law: The Only Winning Move is Not to Play*, THOMPSON HINE (Oct. 15, 2020), https://www.doescrimepay.com/2020/10/algorithms-and-antitrust-law-the-only-winning-move-is-not-to-play/#_ftn7.

[20] UBER, *How Surge Pricing Works*, https://www.uber.com/us/en/drive/driver-app/how-surge-works/ (last visited Oct. 11, 2021). Some commentators allege that Uber's surge pricing will account for low battery to increase customers' fares. Jessica Lindsay, *Does Uber Charge More if Your Battery is Lower?*, METRO (Sept. 27, 2019), https://metro.co.uk/2019/09/27/uber-charge-battery-lower-10778303/.

[21] Jonathan Hall, Cory Kendrick & Chris Nosko, *The Effects of Uber's Surge Pricing: A Case Study*, UBER (2015), https://eng.uber.com/research/the-effects-of-ubers-surge-pricing-a-case-study/.

[22] Meyer v. Kalanick, 174 F. Supp. 3d 817, 820, 822–24 (S.D.N.Y. 2016).

[23] *Id.* at 824.

[24] *Id.* at 825.

[25] Meyer v. Uber Techs., Inc., 868 F.3d 66 (2d Cir. 2017).

[26] Meyer, 174 F. Supp. 3d, at 826 (citing United States v. Ulbricht, 31 F. Supp. 3d 540, 559 (S.D.N.Y. 2014) ("[I]f there were an automated telephone line that offered others the opportunity to gather together to engage in narcotics trafficking by pressing '1,' this would surely be powerful evidence of the button-pusher's agreement to enter the conspiracy. Automation is effected through a human design; here, Ulbricht is alleged to have been the designer of Silk Road.").

Such automation via price-setting models, along with increasing access to comprehensive market information, presents new challenges for antitrust regulators. Algorithmic price-setting opens the door to a series of both intentional and unintentional market distortions.[27] It also opens the door to possible efficiencies that could advance consumer welfare. But distinguishing between market distortions and market efficiencies will be difficult.[28]

Furthermore, algorithmically facilitated anticompetitive conduct in multi-firm interactions may not always be detectable through traditional means. In some cases, interactions between dynamic pricing algorithms may lead to obviously absurd results. For example, two booksellers that both employed Amazon's dynamic pricing algorithm eventually pushed the price of a used textbook to nearly $24 million.[29] But in other cases, pricing algorithms may facilitate less dramatic but no less real collusive price-fixing strategies. In 2015, for instance, a Californian poster and framed art dealer pleaded guilty to coordinating with other art dealers to use price-fixing algorithms to set the price of artworks on Amazon.[30] In that case, the defendant apparently used the algorithm as a tool in an intentional scheme to act anticompetitively. Similarly, in 2016, the U.K. Competition and Markets Authority determined that two competing sellers of licensed sports and entertainment posters infringed upon competition law by agreeing with one another that they would not undercut each other's prices for posters sold on Amazon's U.K. website—and then using automated pricing software to effectuate that agreement.[31] In 2018, the European Commission sanctioned four electronics manufacturers for price-fixing in the consumer retail market.[32] The manufacturers had used a digital algorithm to monitor retailers' pricing to ensure it met the minimum price in their scheme; in turn, the retailers used an automated pricing system to match their competitors' prices.[33]

We do not mean to suggest, of course, that the use of algorithms for setting prices will or should be inherently suspect. Our point is simply that the increasing complexity of business behavior and its reliance on sophisticated digital technology is likely to make the antitrust regulator's task correspondingly complex,

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[27] Chen, Mislove & Wilson, *supra* note 16, at 10.

[28] ORG. FOR ECON. COOP. & DEV., PERSONALIZED PRICING IN THE DIGITAL ERA (Nov. 28, 2018), http://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DAF/COMP(2018)13&docLanguage=En. *See also* Peter Cohen, Robert Hahn, Jonathan Hall, Steven Levitt & Robert Metcalfe, *Using Big Data to Estimate Consumer Surplus: The Case of Uber* (Aug. 30, 2016), https://www.ftc.gov/system/files/documents/public_comments/2018/08/ftc-2018-0048-d-0124-155312.pdf.

[29] 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/.

[30] U.S. DEP'T OF 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; Plea Agreement, United States v. Topkins, CR-15-201 (N.D. Cal. Apr. 30, 2015), https://www.justice.gov/atr/case-document/file/628891/download.

[31] COMPETITION & MKTS. AUTH., DECISION OF THE COMPETITION AND MARKETS AUTHORITY: ONLINE SALES OF POSTERS AND FRAMES – Case 50223 (2016), https://assets.publishing. service.gov.uk/media/57ee7c2740f0b606dc000018/case-50223-final-non-confidential-infringement-decision.pdf. *See generally* ORG. FOR ECON. COOP. & DEV., ALGORITHMS AND COLLUSION—NOTE FROM THE UNITED KINGDOM (2017), https://one.oecd.org/document/DAF/COMP/WD(2017)19/ en/pdf.

[32] Case AT.40465 - ASUS, European Commission Decision (July 24, 2018), https://ec.europa.eu/competition/antitrust/cases/dec_docs/40465/40465_337_3.pdf; *see generally* Rob Nicholls, *Regtech as an Antitrust Enforcement Tool*, 9 J. ANTITRUST ENF'T 135, 141–42 (2021).

[33] Case AT.40465 - ASUS, European Commission Decision (July 24, 2018), https://ec.europa.eu/competition/antitrust/cases/dec_docs/40465/40465_337_3.pdf.

such that the government would benefit from the use of digital technology too.[34] Pricing algorithms represent only one private sector use of new algorithmic tools. Businesses may also be able to leverage algorithms in other creative but anticompetitive ways. For instance, just as multiple businesses might agree to no-poach agreements with one another in order to fix compensation at artificially low levels,[35] businesses might now use salary algorithms to effectuate similar compensation-fixing—and without overt evidence of agreement so long as the companies have not agreed with each other on the use of a single algorithm. In addition, much concern appears today over ways that algorithms might be used by platform firms to engage in subtle forms of self-preferencing behavior, which could well in some cases constitute unlawful anticompetitive conduct.[36] Other new non-price forms of anticompetitive behavior may arise, such as the prospect of firms using automated natural language processing tools to manipulate and fake online consumer reviews in an effort to gain a competitive advantage.[37]

Moreover, with autonomously learning algorithms, it may not only be easier for business owners and managers to fulfill their anticompetitive intentions and actively collude in more subtle ways, but the algorithms themselves may also make collusive decisions independently of any human decision-maker.[38] Such unconscious collusion may come about, for example, if firms rely on a common intermediary algorithm to set prices or if self-learning algorithms interact and learn to collude with one another.[39] From the standpoint of businesses' managers, algorithmically fostered anticompetitive behavior may be completely unconscious, even though its welfare harms would remain just as real for consumers.[40]

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[34] We note, for example, that machine learning has been used successfully to identify when online retailers are themselves using algorithms for dynamic pricing. Chen, Mislove & Wilson, *supra* note 16.

[35] In re High-Tech Emp. Antitrust Litig., 985 F. Supp. 2d 1167 (N.D. Cal. 2013).

[36] *See, e.g.,* Helena Quinn, Kate Brand & Stephan Hunt, *Algorithms: Helping Competition Authorities Be Cognisant of the Harms, Build Their Capabilities and Act*, 3 CONCURRENCES 5, 6 (2021); Daniel A. Hanley, *How Self-Preferencing Can Violate Section 2 of the Sherman Act*, COMPETITION POL'Y INT'L: CPI ANTITRUST CHRON. (June 15, 2021), https://www.competitionpolicyinternational.com/how-self-preferencing-can-violate-section-2-of-the-sherman-act/; Thomas, Höppner, Maximilian Volmar & Philipp Westerhoff, *Online Advertising: The French Competition Decision on Google's Self-Preferencing in Ad Tech,* CONCURRENCES ECOMPETITIONS (Sept. 24, 2021), https://ssrn.com/abstract=3929310.

[37] *See, e.g.,* Justin Johnson & D. Daniel Sokol, *Understanding AI Collusion and Compliance*, in THE CAMBRIDGE HANDBOOK OF COMPLIANCE 881, 889–92 (Benjamin van Rooij & D. Daniel Sokol, eds., 2021).

[38] Algorithms' ability to collude autonomously should not be overstated, nor would such a circumstance necessarily constitute an antitrust violation under current law. *See, e.g., Podcast: How Pricing Algorithms Learn to Collude*, MIT TECH. REV. (Oct. 27, 2021), https://www.technologyreview.com/2021/10/27/1038835/podcast-how-pricing-algorithms-learn-to-collude/ ("These self-learning algorithms don't have understanding, much less mutual understanding, which is really what's required in the context of the law.") (quoting Joseph Harrington); Ulrich Schwalbe, *Algorithms, Machine Learning, and Collusion*, 14 J. COMPETITION L. & ECON. 568 (2018) (arguing that coordinated and tacitly collusive behavior between algorithms is difficult to achieve).

[39] For instance, banks may use algorithms to set their own interest rates relative to benchmark interest rates. If numerous banks used the same algorithm with the same objective functions, antitrust law would need to determine whether the banks came to an improper agreement or merely made unilateral decisions. *See* Jeff Lubitz & Grace Meyer, *LIBOR-Based Financial Instrument Antitrust Action Settles at $21.775 Million,* ISS INSIGHTS (Sept. 2, 2020), https://insights.issgovernance.com/posts/libor-based-financial-instrument-antitrust-action-settles-at-21-775-million/.

[40] The actual likelihood of such algorithm-derived collusion is currently uncertain and debated in the literature. For a concise review of this literature, *see* Johnson & Sokol, *supra* note 37, at 883–85. Moreover, the extent to which such autonomous collusion is or should be deemed illegal remains under discussion. *See, e.g.,* Joseph E. Harrington, *Developing Competition Law for Collusion by Autonomous Artificial Agents*, 14 J. COMPETITION L. & ECON. 331 (2018).

We have presented what is far from an exhaustive list of ways that algorithms are likely to complicate the work of antitrust authorities around the world.[41] We have pointed to automated pricing systems and the prevalence of other kinds of algorithmic market decision-making simply to illustrate how innovations in the private use of algorithms are likely to present new challenges for competition authorities.[42] Private sector use of algorithms in these and other ways will likely make it easier for firms to evade regulators—or at least will make it harder for regulators to distinguish between legal and illegal conduct.[43] We do not claim that private sector deployment of algorithms will always or even often be problematic under existing antitrust law in the United States or elsewhere in the world—nor are we taking any position on whether the substance of antitrust law necessarily should change in light of these technological developments. Rather, our point is that, under nearly any scenario of the future, algorithms will change the conduct of business in ways that will likely prompt governmental authorities to see it necessary to deploy similar algorithmic tools in overseeing the marketplace.

II. Toward Antitrust by Algorithm

We thus see a strong case for regulators to become more versed in using innovative technologies similar to those used by private firms.[44] Just as algorithmic tools have exacerbated the complexity and dynamism of the marketplace and created new challenges for antitrust enforcement, these same technological advances may also help antitrust regulators better pinpoint potential legal violations.[45] The new marketplace will likely put a premium on antitrust

[41] For a more comprehensive discussion of potential competitive and consumer harms from businesses' use of algorithms, see U.K. COMPETITION & MKTS. AUTH., ALGORITHMS: HOW THEY CAN REDUCE COMPETITION AND HARM CONSUMERS (Jan. 19, 2021), https://www.gov.uk/government/publications/algorithms-how-they-can-reduce-competition-and-harm-consumers/algorithms-how-they-can-reduce-competition-and-harm-consumers#contents.

[42] *See, e.g.,* Emilio Calvano, Giacomo Calzolaris, Vincenzo Denicolò & Sergio Pastorello, *Artificial Intelligence, Algorithmic Pricing, and Collusion*, 110 AM. ECON. ASSOC. REV. 3267 (2020), https://www.aeaweb.org/articles?id=10.1257/aer.20190623; 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; Joseph E. Harrington, Jr., *The Effect of Outsourcing Pricing Algorithms on Market Competition* (forthcoming), https://joeharrington5201922.github.io/pdf/Outsourcing%20pricing%20algorithms_21.07.19.pdf.

[43] Antitrust regulators inherently face challenges in detecting unlawful behavior because "effective collusion is clandestine." William E. Kovacic, Robert C. Marshall & Michael J. Meurer, *Serial Collusion by Multi-Product Firms*, 6 J. ANTITRUST ENF'T 296, 298 (2018). But with the ability to make more fine-grained decisions, firms' anti-competitive behavior will likely grow harder for antitrust authorities to detect if they fail to enhance their own analytic capacities. For example, it has been suggested:

> If new technologies make coordinated interaction more likely, competition enforcers will need to focus more on coordinated effects in merger analysis at lower market concentration thresholds. . .. [Algorithmic price discrimination] may increase the chances that a given merger will harm consumers in some relevant market even if the remaining post-merger competition is sufficient to protect the majority of consumers.

Terrell McSweeny & Brian O'Dea, *The Implications of Algorithmic Pricing for Coordinated Effects Analysis and Price Discrimination Markets in Antitrust Enforcement*, 32 ANTITRUST 75, 79 (2017).

[44] As Salil Mehra has noted, "as the competition they oversee becomes more complicated, enforcement agencies will need to develop increased technical competence to understand new forms of algorithmic competition." Salil K. Mehra, *Algorithmic Competition, Collusion, and Price Discrimination*, in THE CAMBRIDGE HANDBOOK OF THE LAW OF ALGORITHMS 199, 205 (Woodrow Barfield, ed., 2020).

[45] *See* Giovanna Massarotto, *Using Tech to Fight Big Tech*, BLOOMBERG L. (Sept. 27, 2021), https://news.bloomberglaw.com/tech-and-telecom-law/using-tech-to-fight-big-tech ("Government's adoption of emerging technologies would help deepen its understanding in the same technologies that now rely on data, and the markets it wants to oversee. The truth is that government could not think of moving

authorities' use of algorithmic tools simply to keep pace with the use of these tools by the private sector.[46]

Some observers have proposed substantive changes to antitrust law that would impose new regulatory responsibilities on dominant firms in the new digital marketplace.[47] Legal authorities around the world have begun to consider legislative and regulatory changes that would impose conduct standards and other affirmative obligations on firms' use of data and digital tools in an effort to combat anticompetitive tendencies. [48] Some of these proposals call for increasing oversight of mergers in the digital sector, establishing new agencies dedicated to certain types of tech firms, and scrutinizing innovation and data use by dominant firms.[49]

Other proposals call for various forms of ex ante conduct regulation, such as mandating data sharing for firms with bottleneck power and mandating data mobility and open standards for all firms.[50] An amendment to the German Competition Act, for example, prohibits self-preferencing by dominant firms and imposes on them affirmative obligations of interoperability and data portability.[51] It

fast enough in its enforcement action without these adequate resources and tools."); Quinn, Brand & Hunt, *supra* note 36, at 10 ("As the number and complexity of digital competition cases grow, so too does the need for competition agencies to have data and technology skills . . . . Without data and technology skills, including algorithmic skills, agencies may struggle to hold dominant technology companies to account.").

[46] Coglianese, *Optimizing Regulation*, *supra* note 2.

[47] *See, e.g.*, Zev Mahari, Robert, Sandro Claudio Lera & Alex Pentland, *Time for a New Antitrust Era: Refocusing Antitrust Law to Invigorate Competition in the 21st Century*, 1 STAN. COMPUTATIONAL ANTITRUST 52 (2021).

[48] For recent analyses and proposals from antitrust authorities around the world, see, e.g., U.K. COMPETITION & MKTS. AUTH., UNLOCKING DIGITAL COMPETITION (2017), https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/785547/unlocking_digital_competition_furman_review_web.pdf; AUSTL. COMPETITION & CONSUMER COMM'N, DIGITAL PLATFORMS INQUIRY: FINAL REPORT (2019), https://www.accc.gov.au/publications/digital-platforms-inquiry-final-report; AUTORITÉ DE LA CONCURRENCE & BUNDESKARTELLAMT, ALGORITHMS AND COMPETITION (2019), https://www.autoritedelaconcurrence.fr/sites/default/files/algorithms-and-competition.pdf; COMPETITION BUREAU CAN., BIG DATA AND INNOVATION: KEY THEMES FOR COMPETITION POLICY IN CANADA (2018), https://www.competitionbureau.gc.ca/eic/site/cb-bc.nsf/vwapj/CB-Report-BigData-Eng.pdf/$file/CB-Report-BigData-Eng.pdf. *See generally* ORG. FOR ECON. COOP. & DEV., ALGORITHMS AND COLLUSION: COMPETITION POLICY IN THE DIGITAL AGE (2017), http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm; JACQUES CRÉMER, YVES-ALEXANDRE DE MONTJOYE & HEIKE SCHWEITZER, EUR. COMM'N, COMPETITION POLICY FOR THE DIGITAL ERA (European Commission, 2019), https://ec.europa.eu/competition/ publications/reports/kd0419345enn.pdf; ANTITRUST L. SECTION, AM. BAR. ASS'N, ARTIFICIAL INTELLIGENCE & MACHINE LEARNING: EMERGING LEGAL AND SELF-REGULATORY CONSIDERATIONS, A REPORT BY THE AMERICAN BAR ASSOCIATION'S SECTION OF ANTITRUST: PART ONE (2019), https://www.americanbar.org/content/dam/aba/administrative/antitrust_law/comments/october-2019/clean-antitrust-ai-report-pt1-093019.pdf [hereinafter "ABA PART ONE"]; ANTITRUST L. SECTION, AM. BAR. ASS'N, COMPETITION IMPLICATIONS OF BIG DATA AND ARTIFICIAL INTELLIGENCE/MACHINE LEARNING, A REPORT BY THE AMERICAN BAR ASSOCIATION'S SECTION OF ANTITRUST: PART TWO (2021), https://www.americanbar.org/content/dam/aba/administrative/antitrust_law/comments/feb-21/aba-big-data-task-force-white-paper-part-two-final-215.pdf.authcheckdam [hereinafter "ABA PART TWO"].

[49] ABA PART TWO, *supra* note 48, at 65–66; STIGLER CTR. FOR THE STUDY OF THE ECON. & THE STATE & UNIV. OF CHI. BOOTH SCH. OF BUS., STIGLER COMM. ON DIGIT. PLATFORMS: FINAL REPORT (2019), https://www.chicagobooth.edu/-/media/research/stigler/pdfs/digital-platforms---committee-report---stigler-center.pdf [hereinafter STIGLER CTR.].

[50] *See, e.g.,* STIGLER CTR., *supra* note 49; Press Release, *Senators Introduce Bipartisan Bill to Encourage Competition in Social Media*, MARK R. WARNER (Oct. 22, 2019), https://www.warner.senate.gov/public/index.cfm/2019/10/senators-introduce-bipartisan-bill-to-encourage-competition-in-social-media; William P. Rogerson & Howard Shelanski, *Antitrust Enforcement, Regulation, and Digital Platforms*, 168 U. PA. L. REV. 1911, 1911–40 (2020).

[51] GESETZ GEGEN WETTBEWERBSBESCHRÄNKUNGEN [GWB] [GERMAN COMPETITION ACT], https://www.gesetze-im-internet.de/englisch_gwb/; see also FED. MINISTRY OF ECON. AFFS. & ENERGY, A NEW

also introduces a new category of market power: companies with "paramount significance for competition across markets," which encompasses digital players that have significant influence on certain markets without having significant market shares in those markets.[52] Dominant firms with financial strength and access to data relevant for competition are prohibited from conduct that creates self-favoring, impedes competitors by leveraging market power, uses data collected in a market in which it is dominant to create or increase barriers to entry in other markets, hinders interoperability and data portability, and provides insufficient information to other firms to evaluate its services.[53]

Regardless of the precise direction that antitrust law should take in the years ahead—a substantive question which we do not address here—competition regulators will need to adapt their operations to respond better to new market conditions and business practices.[54] Already, regulators in domains other than antitrust are discovering the value of big data and machine-learning algorithms for maximizing the impact of their limited enforcement resources.[55] Digital algorithms are being widely used to answer a perennial challenge facing regulators: namely, how to allocate scarce auditing attention optimally among millions of transactions and thousands of firms so as to "find the needles in these haystacks, with limited staff."[56] For example, the U.S. Internal Revenue Service uses algorithmic tools to detect tax evasion[57] and the Centers for Medicare and Medicaid Services uses these tools to identify fraud in the health care sector.[58] The U.S. Securities and Exchange Commission also now uses machine learning to detect instances of securities fraud

COMPETITION FRAMEWORK FOR THE DIGITAL ECONOMY, REPORT BY THE COMMISSION 'COMPETITION LAW 4.0' (2019), https://www.bmwi.de/Redaktion/EN/Publikationen/Wirtschaft/a-new-competition-framework-for-the-digital-economy.pdf?blob=publicationFile&v=3.

[52] GIBSON DUNN, *"Digitalization Act": Significant Changes to German Antitrust Rules* (Jan. 28, 2021), https://www.gibsondunn.com/digitalization-act-significant-changes-to-german-antitrust-rules/.

[53] GWB, *supra* note 51, at § 18, ¶ 2a–3a, § 20, ¶ 3a.

[54] *See* Mehra, *supra* note 44, at 208 ("Antitrust enforcers will have to upgrade their technical skills and improve their ability to gauge empirically whether algorithmically driven practices hurt consumers."). It has even been suggested that, if antitrust authorities can improve their enforcement of traditional antitrust law using advanced technologies, this may reduce to some degree the need for adopting ex ante regulations. *See* Schrepel, *supra* note 1, at 13.

[55] Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 GEO. L.J. 1147 (2017); Cary Coglianese & Lavi Ben Dor, *AI in Adjudication and Administration*, 86 BROOKLYN L. REV. 791 (2021).

[56] Stefan Hunt, *From Maps to Apps: The Power of Machine Learning and Artificial Intelligence for Regulators*, BEESLEY LECTURE SERIES ON REGULATORY ECONOMICS (Oct. 19, 2017), https://www.fca.org.uk/publication/documents/from-maps-to-apps.pdf.

[57] *See* U.S. DEP'T OF TREASURY, Treasury Announces IRA Integrated Modernization Business Plan Promoting Cost Efficiency, Improved Taxpayer Service and Protection (Apr. 18, 2019), https://home.treasury.gov/news/press-releases/sm663 (noting "software that completes laborious tasks in seconds through automation and artificial intelligence, eliminating error-prone manual work and increasing speed and accuracy"); U.S. TREASURY INSPECTOR GEN. FOR TAX ADMIN., The Information Reporting and Document Matching Case Management System Could Not Be Deployed (Sept. 29, 2014), https://www.treasury.gov/tigta/auditreports/2014reports/201420088fr.pdf; *see also* Erik Hemberg, Jacob Rosen, Geoff Warner, Sanith Wijesinghe & Una-May O'Reilly, *Tax Non-Compliance Detection Using Co-Evolution of Tax Evasion Risk and Audit Likelihood*, PROC. 15TH INT'L CONF. ON A.I. & L. at 79 (2015), https://taxprof.typepad.com/files/taxpaper.pdf; Lynnley Browning, *Computer Scientists Wield Artificial Intelligence to Battle Tax Evasion*, N.Y. TIMES (Oct. 9, 2015), https://www.nytimes.com/2015/10/10/business/computer-scientists-wield-artificial-intelligence-to-battle-tax-evasion.html. For a discussion of how other tax authorities are using AI tools, see AI TRENDS, *AI Applied to Tax Systems Can Help Discover Shelters, Support Equality* (Feb. 4, 2021), https://www.aitrends.com/ai-in-government/ai-applied-to-tax-systems-can-help-discover-shelters-support-equality/.

[58] Edward Roche, *The Audit Algorithm Arms Race in Medicare*, RAC MONITOR (Sept. 2, 2020), https://racmonitor.com/the-audit-algorithm-arms-race-in-medicare/.

and insider trading.[59] A survey conducted across the U.S. federal government found that regulators increasingly use AI tools as a means of setting enforcement priorities—indeed, enforcement makes up the second largest category of use cases identified in the survey.[60]

Algorithmic tools have achieved demonstrable improvements in government agencies' ability to forecast accurately—which has also been the main impetus for deploying them in the private sector.[61] For example, machine-learning algorithms have been found to improve the ability of environmental regulators to detect violations of water pollution rules by up to six times that of other methods.[62] Border officials have used them in Greece to detect individuals with asymptomatic cases of COVID-19, improving the identification of such cases by more than two times conventional screening cases.[63] They have been adopted to help in the detection of violations of fisheries' bycatch limitations,[64] the forecasting of recidivism in bail and parole decisions,[65] and choices about where to send building inspectors and general police patrols.[66] It is not hard to foresee an emerging era across government of increasing administrative reliance on "adjudication by algorithm" and even "rulemaking by robot."[67]

Although antitrust authorities do not appear to have moved as quickly to adopt AI tools as have other regulators,[68] they are starting to see value in exploring ways to use the same kinds of innovative computational tools that other governmental authorities are using.[69] The U.K. Competition and Markets Authority, for instance,

[59] DAVID FREEMAN ENGSTROM, DANIEL E. HO, CATHERINE M. SHARKEY & MARIANO-FLORENTINO CUÉLLAR, GOVERNMENT BY ALGORITHM: ARTIFICIAL INTELLIGENCE IN FEDERAL ADMINISTRATIVE AGENCIES 22–29 (2020), https://www-cdn.law.stanford.edu/wp-content/uploads/2020/02/ACUS-AI-Report.pdf.

[60] *Id.* at 17. The largest category was regulatory research, analysis, and monitoring.

[61] For a review of studies showing how machine-learning algorithms can make improvements in the performance of governmental tasks, see Cary Coglianese & Alicia Lai, *Algorithm vs. Algorithm*, 72 DUKE L.J. 1281 (2022). *See also* DANIEL KAHNEMAN, OLIVIER SIBONY, CASS R. SUNSTEIN, NOISE: A FLAW IN HUMAN JUDGMENT (2021).

[62] *See* Miyuki Hino, Elinor Benami & Nina Brooks, *Enhancing Environmental Monitoring Through Machine Learning*, 1 NATURE SUSTAINABILITY 583, 583–84 (2018).

[63] *See Nations can learn from Greece's use of AI to curb COVID-19*, 597 NATURE 447 (2021), https://media.nature.com/original/magazine-assets/d41586-021-02554-y/d41586-021-02554-y.pdf; Hamsa Bastini, et al., *Efficient and Targeted COVID-19 Border Testing via Reinforcement Learning,* 599 NATURE 108 (2021).

[64] *See* Richard Berk, *Forecasting Consumer Safety Violations and Violators*, in IMPORT SAFETY: REGULATORY GOVERNANCE IN THE GLOBAL ECONOMY 131 (Cary Coglianese, Adam M. Finkel & David Zaring eds., 2009).

[65] *See* Richard Berk, Lawrence Sherman, Geoffrey Barnes, Ellen Kurtz & Lindsay Ahlman, *Forecasting Murder Within a Population of Probationers and Parolees: A High Stakes Application of Statistical Learning*, 172 J. ROYAL STAT. SOC'Y SERIES A 191 (2009).

[66] *See* Coglianese & Lehr, *supra* note 55.

[67] *Id.*; *see also* LAW AS DATA: COMPUTATION, TEXT, AND THE FUTURE OF LEGAL ANALYSIS (Michael A. Livermore & Daniel N. Rockmore eds., 2019); OMRI BEN-SHAHAR & ARIEL PORAT, PERSONALIZED LAW: DIFFERENT RULES FOR DIFFERENT PEOPLE (2021).

[68] *See* Ai Deng, *An Antitrust Lawyer's Guide to Machine Learning*, 32 ANTITRUST 82, 82 (2017) ("The antitrust community is largely playing catch-up on technical aspects of AI and ML.")

[69] The U.S. Department of Justice's Antitrust Division, for example, has undertaken efforts to "increase the division's capabilities and engagement in emerging technologies relevant to antitrust enforcement." Press Release, Justice Department Joins Computational Antitrust Project at Stanford Law School, U.S. Dep't. of Just. (Jan. 19, 2021), https://www.justice.gov/opa/pr/justice-department-joins-computational-antitrust-project-stanford-law-school. Similarly, the European Commission has initiated research "on how Artificial Intelligence could potentially improve DG Competition's processes of evidence management, legal drafting, and market intelligence gathering." EUR. COMM'N: COMPETITION POL'Y, Ex-ante publicity on low and middle value contracts, https://ec.europa.eu/competition-policy/single-market-programme-smp/calls-tenders-contracts/ex-ante-publicity-low-and-middle-value_en (last

is pursuing the use of algorithmic techniques and other efforts "to understand how firms are using data, what their machine learning (ML) and AI algorithms are doing, the consequences of these algorithms and, ultimately, what actions authorities need to take."[70]

Interest in algorithmic tools is also growing among antitrust legal scholars who are identifying possible ways to supplement—or even at times supplant—traditional approaches to antitrust regulation and enforcement through the use of AI and blockchain technologies. Thibault Schrepel, for example, has issued what can be considered a manifesto for antitrust by algorithm, arguing that, as "markets are becoming increasingly complex and dynamic in today's economy[, t]his complicates the task of antitrust agencies, each day a little more."[71] Schrepel explains that, "[a]gainst this background, the implementation of computational methods is becoming necessary to maintain and improve antitrust agencies' ability to detect, analyze, and remedy anticompetitive practices."[72] He specifically points to the potential for new digital technologies to enable antitrust regulators to process vast quantities of data and large volumes of text more quickly and more effectively.[73] He also argues that advances in information technology and data analytics may make possible substantial improvements to real-time, dynamic analyses of mergers.[74]

The growing interest by legal scholars in the use of AI tools for antitrust parallels an increasing recognition by economists in the value of using more sophisticated, dynamic analysis to assess market competitiveness and to identify rent-seeking behavior.[75] Economists have relied on machine learning to help enhance their market analyses, whether in estimating counterfactuals or solving dynamic games.[76]

Of course, even with an increasing recognition of how machine learning can improve economic analysis, economists and government regulators will not find that every question can be answered best by machine learning.[77] Analyses of well-

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visited Nov. 1, 2021). In the Netherlands, authorities have developed a predictive analytics tool to identify sectors with potential market concentration problems. Lilian Petit, *The Economic Detection Instrument of the Netherlands Competition Authority: The Competition Index* (NMa Working Paper No. 6, 2012), https://ssrn.com/abstract=1992774.

[70] U.K. COMPETITION & MKTS. AUTH.: CMA BLOG, CMA's new DaTA unit: exciting opportunities for data scientists (Oct. 24, 2018), https://competitionandmarkets.blog.gov.uk/2018/10/24/cmas-new-data-unit-exciting-opportunities-for-data-scientists/.

[71] Schrepel, *supra* note 1, at 4.

[72] *Id.*

[73] *Id.* at 5–7.

[74] *Id.* at 8–9.

[75] For decades, economists have recognized the need for dynamic modeling of firms' competitive behavior. Victor Aguirregabiria & Aviv Nevo, *Recent Developments in Empirical IO: Dynamic Demand and Dynamic Games*, ADVANCES IN ECONOMICS & ECONOMETRICS 53 (Daron Acemoglu, Manuel Arellano & Eddie Dekel eds., 2013). Economists are increasingly exploring the role that machine learning can play in such dynamic analysis. Victor Aguirregabiria, Allan Collard-Wexler & Stephen P. Ryan, *Dynamic Games in Empirical Industrial Organization*, ARXIV:2109.01725 [ECON.EM] (2021).

[76] Hal R. Varian, *Big Data: New Tricks for Econometrics*, 28 J. ECON. PERSPS. 3 (2014); Sendhil Mullainathan & Jan Spiess, *Machine Learning: An Applied Econometric Approach*, 31 J. ECON. PERSPS. 87 (2017); Susan Athey, *The Impact of Machine Learning on Economics*, in THE ECONOMICS OF ARTIFICIAL INTELLIGENCE: AN AGENDA (Univ. of Chicago Press, 2019); Aguirregabiria & Nevo, *supra* note 75, at 52–56; Feder Iskhakov, John Rust & Bertel Schjerning, *Machine learning and structural econometrics: contrasts and synergies*, 23 THE ECONOMETRICS J. S81 (2020).

[77] For reasons to be cautious about how much to expect machine learning can achieve in the economic analysis of competition, see Aguirregabiria & Nevo, *supra* note 75, at 52–56.

studied sectors can be, and likely will still be, best approached using other analytic techniques.[78] Moreover, data limitations will prove an impediment to the use of machine-learning algorithms in many contexts.

Nevertheless, assuming data availability, machine learning does promise to be helpful for identifying patterns that deserve greater antitrust scrutiny.[79] Firms themselves are said to find these algorithms useful to support their own internal compliance management systems.[80] Machine-learning algorithms may be especially useful for public regulators in monitoring market behaviors and outcomes in newer, data-rich settings where existing economic theory remains limited—a category of business that seems only destined to grow larger in the years ahead.[81] Machine learning is also likely to facilitate improvements in antitrust regulators' decision-making about how to target scarce resources for enforcement investigation.[82]

In an increasingly complex, dynamic market environment, antitrust authorities will need better ways to identify problems and problematic behavior by firms. Even when machine-learning tools cannot by themselves support authoritative judgments of market concentration or anticompetitive behavior, they are likely to be able to help regulators determine where to look more closely by identifying anomalies in pricing and other market behavior, or by relying on various proxies to forecast likely perpetrators of collusive conduct.[83] Overall, market imperatives and technological capabilities will increasingly point antitrust authorities toward greater reliance on the use of machine-learning algorithms to carry out their missions.

III. Antitrust by Algorithm's Institutional Challenges

Initial exploration of the use of algorithmic tools is currently possible for many antitrust authorities, and some competition bodies are already starting to make incremental moves to enhance their reliance on computational technology.[84] It is thus no longer difficult to imagine a qualitatively distinct future in which antitrust

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[78] With sufficient data, of course, even the behavior of long-established lines of businesses can be illuminated with machine learning. *See, e.g.*, Tianyi Wang et al., *A Framework for Airfare Price Prediction: A Machine Learning Approach*, IEEE 20TH INT'L CONF. ON INFO. REUSE & INTEGRATION FOR DATA SCI. (2019).
[79] Deng, *supra* note 68, at 84 (discussing how AI tools "might be used to deter and prevent cartel formation").
[80] Sabine Zigelski & Lynn Robertson, *What Can Make Competition Compliance Programmes Really Effective?*, COMPETITION POL'Y INT'L: CPI ANTITRUST CHRON. (Nov. 16, 2021) ("Algorithms can support businesses in their monitoring, prevention and detection efforts, which can benefit from widely available know-how on screening for anti-competitive behaviours."); ORG. FOR ECON. COOP. & DEV., COMPETITION COMPLIANCE PROGRAMMES 40 (2021), https://www.oecd.org/daf/competition/competition-compliance-programmes-2021.pdf ("In addition to structural, price or performance-based screens, companies can use Artificial Intelligence (AI) to monitor company communication for suspicious signs, such as keywords in competitor communication, which can lead to an early flagging of potentially problematic behaviour."). *See also* Deputy Assistant Attorney General Matthew S. Minor, Remarks at the 6th Annual Government Enforcement Institute, U.S. DEP'T OF JUST. (Sept. 12, 2019), https://www.justice.gov/opa/speech/deputy-assistant-attorney-general-matthew-s-miner-delivers-remarks-6th-annual-government (noting that in the enforcement setting prosecutors in financial cases will ask "about what the company has done to analyze or track its own data resources").
[81] *Cf*. Massarotto, *supra* note 45.
[82] *See, e.g.*, Nicholls, *supra* note 32; Giovanna Massarotto & Ashwin Ittoo, *Gleaning Insight from Antitrust Cases Using Machine Learning*, 1 STAN. COMPUTATIONAL ANTITRUST 16 (2021); Martin Huber & David Imhof, *Machine Learning with Screens for Detecting Bid-Rigging Cartels*, 65 INT'L J. INDUS. ORG. 277 (2019).
[83] Joseph E. Harrington, Jr., *Detecting Cartels*, in HANDBOOK OF ANTITRUST ECONOMICS 213, 252 (2006) (suggesting value in finding "new empirical methods for picking up structural change and statistical anomalies . . . for identifying markets worthy of closer scrutiny").
[84] Massarotto & Ittoo, *supra* note 82.

regulators, as with regulators more generally, come to rely much more extensively on machine learning to automate tasks and functions currently handled by humans.[85] Indeed, for the reasons we have outlined, it seems apparent that moving toward substantial reliance on artificial intelligence to oversee market behavior—that is, toward antitrust by algorithm—will be a sensible strategy if authorities are to fulfill antitrust's goals in a marketplace driven itself by algorithms. But making significant changes to reorganize and reconceive antitrust oversight in an algorithmic era will not be easy. As we have noted, antitrust authorities may well need to be given new legislative authorities and the substantive nature of antitrust law may need to be rewritten to some degree.[86] Regardless of any substantive changes to the law, antitrust bodies will also need the leadership vision and resources to overcome a series of institutional challenges in making a transition to antitrust by algorithm.

As much as the rationale for antitrust authorities' pursuit of machine learning can be readily understood in general terms given changes in market dynamics, the managers of antitrust authorities will need to make a series of concrete decisions about exactly when and for what purposes to use specific kinds of algorithmic tools, as well as how those tools should be designed and deployed. In making these decisions, managers should obviously focus in the first instance on whether the use of algorithmic tools will improve their organizations' performance in terms of fulfilling their market oversight missions. Especially if automated tools are to replace humans in the performance of certain tasks or functions, the guiding question should be whether the digital algorithms can perform better than trained humans—with "better" operationalized in terms of outcomes specified by the antitrust organization's leaders, including increased accuracy and speed in spotting collusion or other rent-seeking behavior.[87]

A variety of factors will affect machine-learning algorithms' performance at tasks within antitrust organizations. Some factors are inherent in how algorithms function: they require large volumes of reliable and relevant data along with well-specified, mathematically stated goals.[88] If these inherent preconditions for using algorithmic tools cannot be met, then antitrust authorities will not be able to deploy them to their advantage. For example, in situations where market conditions are rapidly changing, it will be imperative for the antitrust regulator to have a steady supply of current data, or else the algorithm will suffer from "brittleness"—a problem of external validity.[89]

In noting the need for data, we do not mean to suggest that the amount of—or even the currency of—data available to antitrust authorities will be an exogenous

[85] Coglianese & Lehr, *supra* note 55.
[86] *See supra* Part II.
[87] Coglianese & Lai, *supra* note 61.
[88] For discussion of the importance of goal precision in the context of the analysis of mergers, see Anthony J. Casey & Anthony Niblett, *Micro-Directives and Computational Merger Review*, 1 STAN. J. COMPUTATIONAL ANTITRUST 132 (2021). *See generally* Cary Coglianese, *Algorithmic Regulation: Machine Learning as a Governance Tool*, in MARC SCHUILENBURG & RIK PEETERS, EDS., THE ALGORITHMIC SOCIETY: TECHNOLOGY, POWER, AND KNOWLEDGE 35, 47–49 (2021); Coglianese & Lehr, *supra* note 55, at 1215 n. 283, 1218.
[89] Of course, it bears noting that if conditions are indeed rapidly changing, then relying on traditional tools may well be even more brittle, with machine learning still performing comparatively better.

condition out of an antitrust authority's control. On the contrary, data availability, like other resources, may be adjustable and will be just one of the institutional challenges that authorities will face in shifting toward an era of antitrust by algorithm. Overall, authorities will need to address three types of institutional challenges which we identify in this final part of this paper: (a) building their organizations' capacities to make effective and responsible use of advances in predictive analytics; (b) avoiding legal pitfalls and challenges to governmental reliance on artificial intelligence; and (c) ensuring public confidence and trust in their use of algorithmic tools. These institutional challenges are interconnected. Antitrust authorities will need to build sufficient organizational capacity if they are to use artificial intelligence tools responsibly, which will help in building trust and overcoming any legal challenges.

A – Building Organizational Capacity

Data availability will be the first organizational capacity hurdle that antitrust authorities must overcome. If antitrust by algorithm is justified by the rapid pace of market activity—including activity driven itself by private actors' use of algorithms—then antitrust regulators will almost surely need data access at a speed that mirrors the market activity the regulators are seeking to oversee. To obtain this access, antitrust officials could insist on including real-time sharing of digital data on a case-by-case basis as part of the settlement agreements they negotiate in enforcement actions taken against firms.[90] More generally, some firms might be persuaded to provide such data access voluntarily on a regular basis.[91] But perhaps more likely, legislatures or antitrust agencies will need to establish legal requirements for data-sharing to ensure that all firms provide necessary data access to antitrust authorities.[92]

Access to necessary data, though, is only part of the overall capacity needed by antitrust organizations if they are to transform significantly in their reliance on artificial intelligence. Organizations also need hardware and cloud computing capacity to store and analyze these massive quantities of data. Although the dramatic advances in computing power in recent decades are precisely what have made the machine-learning revolution feasible, many governmental IT systems nevertheless remain significantly older, even antiquated.[93] Moreover, governments not only need up-to-date hardware for data storage and analysis; they also need to invest in the technologies and operational procedures required for robust privacy

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[90] Harrington, *supra* note 83, at 252.

[91] *Cf.* Cary Coglianese, Richard Zeckhauser & Edward Parson, *Seeking Truth for Power: Informational Strategy and Regulatory Policy Making*, 89 MINN. L. REV. 277 (2004).

[92] Geoffrey G. Parker, Georgios Petropoulos & Marshall W. Van Alstyne, *Digital Platforms and Antitrust*, *in* OXFORD HANDBOOK OF TRANSNATIONAL ECONOMIC GOVERNANCE (Eric Brousseau, Jean-Michel Glachant & Jérôme Sgard eds., 2022), https://www.bruegel.org/wp-content/uploads/2020/11/WP-2020-06-1.pdf; Schrepel, *supra* note 1, at 6. Because many of the most significant businesses subject to antitrust scrutiny in the years ahead will have a transnational scope, international regulatory cooperation and even data-sharing will also be important.

[93] DONALD F. KETTL, ESCAPING JURASSIC GOVERNMENT: HOW TO RECOVER AMERICA'S LOST COMMITMENT TO COMPETENCE (2016); Jack Moore, *The Crisis in Federal IT that's Scarier than Y2K Ever Was*, NEXTGOV (Nov. 20, 2015), http://www.nextgov.com/cio-briefing/2015/11/crisis-federal-it-rivals-y2k/123908/; U.S. GOV'T ACCOUNTABILITY OFF., GAO-16-696T, Federal Agencies Need to Address Aging Legacy Systems: Hearing Before the H. Comm. on Oversight and Gov't Reform, 114th Cong. (2016), https://www.gao.gov/assets/680/677454.pdf (testimony of David A. Powner, Director, Information Technology Management Issues).

and cybersecurity protection of all the data they use.[94] Here, too, governments' current capacity has generally been lacking, with vulnerabilities that antitrust authorities will need to guard against in their data operations.[95]

Antitrust authorities will need adequate human capital and expertise as well.[96] Even though machine learning is usually referred to as artificial intelligence, self-learning analysis still depends vitally on humans to program and structure algorithms, as well as to train, test, validate, and refine them.[97] Antitrust authorities—which already do have staffs of economists and other analysts—will need to ensure that these analytic personnel also possess the latest data science skills as well as exhibit appropriate sensitivity to legal and ethical issues presented by governmental use of artificial intelligence. It will always be challenging to build or maintain an in-house workforce with cutting-edge analytic skills, as public sector organizations face inherent competitive disadvantages vis-à-vis the private sector when it comes to recruiting expertise.[98] When antitrust authorities rely on private contractors and consulting firms to provide necessary human capital to support algorithmic antitrust tools, they must ensure that their procurement contracts protect their organizations and ensure sufficient access to information that may need to be disclosed in litigation or in response to other public oversight demands.[99]

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[94] A variety of government computing systems have been breached in recent years by hackers, terrorist groups, or other countries. *See, e.g.*, Davey Winder, *New Orleans Declares State of Emergency Following Cyber Attack*, FORBES (Dec. 14, 2019), https://www.forbes.com/sites/daveywinder/2019/12/14/new-orleans-declares-state-of-emergency-following-cyber-attack/ (New Orleans); Kate Fazzini, *Alarm in Texas as 23 Towns Hit by 'Coordinated' Ransomware Attack*, CNBC (Aug. 19, 2019), https://www.cnbc.com/2019/08/19/alarm-in-texas-as-23-towns-hit-by-coordinated-ransomware-attack.html (Texas); Allison Ross & Ben Leonard, *Ransomware Attacks Put Florida Governments on Alert*, TAMPA BAY TIMES (June 28, 2019), https://www.tampabay.com/florida-politics/buzz/2019/06/28/ransomware-attacks-put-florida-governments-on-alert/ (Florida); Sarah Hammond, *Houston County Board of Education Website Hit With Ransomware Attack*, 13WMAZ (Sept. 24, 2019), https://www.13wmaz.com/article/news/local/houston-county-board-of-education-website-hit-with-ransomware-attack/93-dece14ea-9fef-4c3b-a913-ea972c5b46fc (Houston); Alan Blinder & Nicole Perlroth, *A Cyberattack Hobbles Atlanta, and Security Experts Shudder*, N.Y. TIMES (Mar. 27, 2018), https://www.nytimes.com/2018/03/27/us/cyberattack-atlanta-ransomware.html (Atlanta); Brendan I. Koerner, *Inside the Cyberattack That Shocked the U.S. Government*, WIRED (Oct. 23, 2016), https://www.wired.com/2016/10/inside-cyberattack-shocked-us-government/. Data on private commercial activity—that is, the kind of data on which an antitrust regulator would rely for machine-learning analysis—might well prove to be an especially valuable target for hackers.

[95] Across the federal government in the United States, for example, "many agencies and critical infrastructure entities continue to face challenges in safeguarding their information systems and information." U.S. GOV'T ACCOUNTABILITY OFF., Federal Government Needs to Urgently Pursue Critical Actions to Address Major Cybersecurity Challenges 10 (2021), https://www.gao.gov/assets/gao-21-288.pdf. A presidential order acknowledges that "[t]he United States faces persistent and increasingly sophisticated malicious cyber campaigns that threaten the public sector ..." and that "[t]he Federal Government must improve its efforts to identify, deter, protect against, detect, and respond to these actions and actors." Exec. Order No. 14,028, 86 Fed. Reg. 26,633 (May 12, 2021).

[96] For a general discussion of the need to build up the human capital within antitrust agencies, see Alison Jones & William E. Kovacic, *Antitrust's Implementation Blind Side: Challenges to Major Expansion of U.S. Competition Policy,* 65 ANTITRUST BULL. 227, 247–48 (2020).

[97] David Lehr & Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. DAVIS L. REV. 653 (2017).

[98] On the challenges of meeting government agencies' need for human expertise, see Coglianese, *Optimizing Regulation*, *supra* note 2, at 10; Eric Katz, *The Federal Government Has Gotten Slower at Hiring New Employees for 5 Consecutive Years*, GOV'T EXEC. (Mar. 1, 2018), https://www.govexec.com/management/2018/03/federal-government-has-gotten-slower-hiring-new-employees-five-consecutive-years/146348/.

[99] *See* Cary Coglianese & Eric Lampmann, *Contracting for Algorithmic Accountability*, 6 ADMIN. L. REV. ACCORD 175 (2021); David S. Rubenstein, *Acquiring Ethical AI*, 73 FLA. L. REV. 747 (2021); Cary Coglianese & Lavi M. Ben Dor, *Procurement as AI Governance*, 2 IEEE TRANSACTIONS ON TECH. & SOC'Y 192 (2021).

B – Avoiding Legal Pitfalls

Outside of the antitrust context, legal conflicts and public controversies have already arisen over governmental use of algorithmic tools.[100] Antitrust authorities should prepare for similar disputes whenever they make a significant shift to relying on algorithmic tools.[101] The range of legal issues that antitrust by algorithm will implicate parallel those that arise with administrative use of machine learning more generally: accountability, transparency, equality, privacy, and due process.[102] Although antitrust authorities, like other governmental entities, will likely often enjoy a practical, if not legal, advantage in court, their prospects of prevailing in court will depend on the law in the specific jurisdictions in which they reside, the particularities of their use of machine-learning algorithms, and the performance of specific algorithmic tools.[103]

But to generalize: When these tools are used to support discretionary actions—for example, general background research—algorithms will pose the least amount of legal risk for antitrust regulators. Similarly, when machine learning is used simply to identify potential firms to target for human follow-up and investigation, these uses are likely to escape judicial interference, especially when human-gathered and human-analyzed evidence forms the actual basis for any subsequently imposed enforcement penalties.[104] Perhaps for this same reason, wherever machine-learning algorithms are used merely to supplement, rather than

[100] In the United States, lawsuits have been filed challenging governments' use of algorithms for making criminal justice determinations, evaluating the performance of public-school teachers, and administering social welfare programs. *See* State v. Loomis, 881 N.W.2d 749 (Wis. 2016); Hous. Fed'n of Teachers, Local 2415 v. Hous. Indep. Sch. Dist., 251 F. Supp. 3d 1168 (S.D. Tex. 2017); K.W. v. Armstrong, 298 F.R.D. 479, 494 (D. Idaho Mar. 25, 2014); Schultz v. Armstrong, No. 3:12-CV-00058-BLW, 2012 WL 3201223 (D. Idaho Aug. 2, 2012). *See generally* Coglianese & Ben Dor, *supra* note 55. Around the world, public controversies have arisen over algorithms in facial recognition systems used by law enforcement officials, public university admissions decisions, and public welfare fraud software, among others. *See, e.g.*, Rachel Metz, *Facial Recognition Tech Has Been Widely Used Across the US Government for Years, a New* Report Shows, CNN (June 30, 2021), https://www.cnn.com/2021/06/30/tech/government-facial-recognition-use-gao-report/index.html; OFQUAL, AWARDING GCSE, AS, A LEVEL, ADVANCED EXTENSION AWARDS AND EXTENDED PROJECT QUALIFICATIONS IN SUMMER 2020: INTERIM REPORT (2020), https://www.gov.uk/government/publications/awarding-gcse-as-a-levels-in-summer-2020-interim-report; Luke Henriques-Gomes, *Robodebt Class Action: Coalition Agrees to Pay $1.2bn to Settle Lawsuit*, THE GUARDIAN (Nov. 16, 2020), https://www.theguardian.com/australia-news/2020/nov/16/robodebt-class-action-coalition-agrees-to-pay-12bn-to-settle-lawsuit; Justine N. Stefanelli, *Netherlands District Court Rules Benefits Fraud Detection Tool Violates Human Rights Comments*, AM. SOC. INT'L. L. (Feb. 6, 2020), https://www.asil.org/ILIB/netherlands-district-court-rules-benefits-fraud-detection-tool-violates-human-rights; Allie Gross, *Update: UIA Lawsuit Shows How the State Criminalizes the Unemployed*, DETROIT METRO TIMES (Oct. 5, 2015), https://www.metrotimes.com/news-hits/archives/2015/10/05/uia-lawsuit-shows-how-the-state-criminalizes-the-unemployed.

[101] For a general discussion of litigation risks associated with governmental use of algorithmic tools, see Coglianese & Lai, *supra* note 61, at 1336–39.

[102] Steven M. Appel & Cary Coglianese, *Algorithmic Governance and Administrative Law*, *in* THE CAMBRIDGE HANDBOOK OF THE LAW OF ALGORITHMS 162 (Woodrow Barfield ed., 2020).

[103] The United States, for example, is widely viewed as having a distinctively adversarial legalistic approach to public policy and administration. ROBERT A. KAGAN, ADVERSARIAL LEGALISM: THE AMERICAN WAY OF LAW (2d ed. 2019). Nevertheless, federal courts tend to defer to administrative agencies in highly technical or scientific matters, which challenges to the use of advanced algorithms in antitrust matters would certainly involve. ADRIAN VERMEULE, LAW'S ABNEGATION: FROM LAW'S EMPIRE TO THE ADMINISTRATIVE STATE 34 (2016).

[104] In the United States, enforcement discretion is treated as "committed to agency discretion" and hence not ordinarily reviewable by courts. Heckler v. Chaney, 470 U.S. 821 (1985). For a discussion of the reviewability of algorithmic selection of enforcement targets, see Coglianese & Lehr, *supra* note 55, at 1169–70.

replace, any kind of human decision-making by antitrust officials, they will likely be less susceptible to reversal by the courts.[105]

Transparency and due process considerations are nevertheless likely to loom large in any lawsuits that are filed challenging antitrust by algorithm. Machine-learning algorithms can achieve highly accurate forecasts but it is not easy for humans to understand or intuitively explain how these algorithms reach their predictions.[106] These algorithms also typically do not directly support causal or even correlative claims—that is, conclusions that businesses with certain characteristics or behaviors are more likely to engage in anticompetitive behavior.[107] Nevertheless, in some countries it may be legally sufficient for antitrust authorities to release only relatively limited information about their algorithms—limited, in some cases, to only the objective functions and general structures—or even to be exempt altogether from disclosing any information if the algorithms are used for law enforcement purposes.[108] But even in these jurisdictions, the law may change, as it has in some countries to date. Under the 2016 European General Data Protection Regulation, for example, businesses that are subjected to algorithmic tools deployed by antitrust authorities will enjoy at least some right to an explanation of how these algorithms work.[109]

Furthermore, some of the same concerns that stand behind calls for consumer protection regulation of artificial intelligence in the private sector may apply whenever the government uses algorithms for consequential purposes. If antitrust or consumer protection agencies demand disclosure of information related to private firms' use of algorithms, they might reasonably expect that the public will demand similar disclosures of their own use of algorithms. It is unsurprising, for example, that the European Commission's 2021 proposal for AI regulation would apply to both private and public sector uses of artificial intelligence.[110]

Antitrust regulators may also face legal challenges related to algorithmic bias, especially should their own algorithms lead to outcomes that unfairly impose disproportionate impacts on businesses owned by women or members of certain racial or religious groups.[111] The potential for algorithmic bias has given rise to a

[105] In the signature legal case in the United States raising due process challenges to governmental reliance of an algorithm, the Wisconsin Supreme Court rejected the challenge on the ground that the results from the algorithm were not determinative of the governmental judgment but merely an aid to a human decision. State v. Loomis, 881 N.W.2d 749 (Wis. 2016).

[106] Cary Coglianese & David Lehr, *Transparency and Algorithmic Governance*, 71 ADMIN. L. REV. 1, 16–18 (2019).

[107] *Id.* at 4–5, 16–17; *see also* Alicia Lai, *Artificial Intelligence, LLC: Corporate Personhood as Tort Reform*, 2021 MICH. ST. L. REV. 597 (2021).

[108] Current federal law in the United States would fit this description of minimal disclosure, or even an exemption altogether, for algorithms used for law enforcement purposes. Coglianese & Lehr, *supra* note 55; at 1205–13; Coglianese & Lehr, *supra* note 106; *see also* Christopher S. Yoo & Alicia Lai, *Regulation of Algorithmic Tools in the United States*, 13 J.L. & ECON. REG. 7 (2020).

[109] Council Regulation 2016/679, 2016 O.J. (L 119) art. 13. The GDPR also provides for a right to a human decision, which will limit European antitrust authorities' ability to implement fully automated, human-out-of-the-loop systems in the future. *Id.* at art. 22 ("The data subject shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her.").

[110] *Commission Proposal for a Regulation of the European Parliament and of the Council Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act) and Amending Certain Union Legislative Acts*, COM (2021) 206 final (Apr. 21, 2021).

[111] For a general discussion, see Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CAL. L. REV. 671 (2016); Coglianese & Lehr, *supra* note 55. For an especially helpful treatment of algorithmic fairness in the

considerable degree of legal and public concern in other contexts, especially when machine-learning algorithms are trained on data that are already infused with human biases.[112] Such concern is most palpable with algorithms trained on general law enforcement data, because crime data are infused with historical, human-created biases.[113] In addition, algorithmic bias is a particular concern in settings where individuals rather than organizations are directly affected or targeted by algorithms.[114] For these reasons, algorithmic bias may seem, at least at first glance, less of a concern with the algorithmic tools likely to be used by antitrust authorities.[115] Nevertheless, given the importance and salience of concerns of algorithmic bias, it would be prudent for antitrust analysts and decision-makers to address these concerns when pursuing antitrust by algorithm.[116]

C – Ensuring Public Trust

Antitrust by algorithm's very promise for advancing the goals of competition law in a dynamic market environment makes it important for antitrust regulators to exercise prudence as they move forward with greater reliance on algorithmic tools. Although antitrust law and its administration might have once seemed largely a technical regulatory domain of interest to a specialized group of lawyers, economists, and academics, today the field of antitrust is much more publicly salient and contested than it has been for decades.[117] When increased public interest in antitrust law is paired with the existence of palpable public concerns about the fairness and transparency of artificial intelligence,[118] it is clear that regulators' overarching approach to antitrust by algorithm must be thoughtfully executed with appropriate validation, transparency, and public consultation. If governmental efforts to pursue computational antitrust are too hastily pursued—or are mismanaged or inadequately overseen—unintended problems or controversy may set back progress in the responsible and effective deployment of computational antitrust.[119]

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criminal justice setting, see Richard Berk, Hoda Heidari, Shahin Jabbari, Michael Kearns & Aaron Roth, *Fairness in Criminal Justice Risk Assessments: The State of the Art*, 50 SOCIO. METHODS & RSCH. 3 (2018).

[112] Sandra G. Mayson, *Bias In, Bias Out*, 128 YALE L.J. 2218, 2122 (2019).

[113] Dorothy E. Roberts, *Digitizing the Carceral State*, 132 HARV. L. REV. 1695 (2019).

[114] *See, e.g.*, VIRGINIA EUBANKS, AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR (2018); SAFIYA UMOJA NOBLE, ALGORITHMS OF OPPRESSION: HOW SEARCH ENGINES REINFORCE RACISM (2018); FRANK PASQUALE, THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION (2015).

[115] In the United States, constitutional principles of equal protection probably do not stand in the way of federal antitrust authorities' use of machine-learning algorithms—absent clear evidence of racial animus. *See* Coglianese & Lehr, *supra* note 55, at 1191–1205.

[116] Rebecca Kelly Slaughter, Janice Kopec & Mohammad Batal, *Algorithms and Economic Justice: A Taxonomy of Harms and a Path Forward for the Federal Trade Commission*, 23 YALE J. L. & TECH. 1 (2021), https://law.yale.edu/sites/default/files/area/center/isp/documents/algorithms_and_economic_justice_master_final.pdf.

[117] *See* Spencer Weber Waller & Jacob E. Morse, *The Political Face of Antitrust*, 15 BROOKLYN J. CORP., FIN. & COM. L. 75 (2020), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3660946 ("After decades of languishing as a relatively technical legal specialty, issues of corporate concentration, income inequality, abuse of dominance and power, and the harms of lenient merger policy have returned as issues of public discussion and debate."); Daniel A. Crane, *Antitrust's Unconventional Politics*, 104 VA. L. REV. ONLINE 118, 120 (2018) (noting the "rising tide of calls for a radically different version of antitrust").

[118] NICOLE GILLESPIE, STEVE LOCKEY & CAITLIN CURTIS, TRUST IN ARTIFICIAL INTELLIGENCE: A FIVE COUNTRY STUDY (2021), https://assets.kpmg/content/dam/kpmg/au/pdf/2021/trust-in-ai-multiple-countries.pdf (reporting that in five countries, including the United States, only 28 percent of survey respondents overall are willing to trust artificial intelligence and no more than about 60 percent have confidence that business and government can "use and regulate antitrust and govern AI in the best interest of the public").

[119] For background on public trust as it pertains to artificial intelligence, see Brian Stanton & Theodore Jensen, National Institute of Standards and Technology, Trust and Artificial Intelligence, NISTIR 8330

In developing and relying on algorithmic tools, antitrust authorities should also account for emerging principles and best practices for public sector entities' responsible use of artificial intelligence. As the Organization for Economic Cooperation and Development (OECD) has noted, uses "of AI in the public sector present challenges, as public administrations must ensure a high standard of transparency and accountability for their actions, especially those that directly impact individuals."[120] The OECD has adopted a series of principles for the responsible use of artificial intelligence that, among other things, calls upon government officials to "commit to transparency and responsible disclosure regarding AI systems" and "to enable those affected by an AI system to understand the outcome" that it generates and challenge any adverse decisions that result from its use.[121] Similar recommendations and guidance have been offered around the world in recent years by governmental authorities, industry groups, and nongovernmental standard-setting bodies.[122]

In moving toward antitrust by algorithm, government officials should begin by engaging in their own basic decision analysis before launching into the design and development of a tool or system that relies on machine-learning analysis.[123] Most importantly, they should focus on whether a contemplated system or tool would likely improve their oversight of industry.[124] In other words, they should ask: What might be some of the strengths, weaknesses, opportunities, and threats associated with a proposed AI system or tool?[125] It will almost certainly be prudent for antitrust authorities to start off small, gaining experience with such tools on uses with lower stakes before attempting to apply them to matters of high stakes.

Algorithmic impact assessments and algorithmic auditing are increasingly considered to be best practices in both private and public sector deployment of

(Dec. 2020), https://tsapps.nist.gov/publication/get_pdf.cfm?pub_id=931087. For considerations of due process in the antitrust context, see Christopher S. Yoo, Thomas Fetzer, Shan Jiang, & Yong Huang, *Due Process in Antitrust Enforcement: Normative and Comparative Perspectives*, 94 S. CAL. L. REV. 843 (2021).

120 ORG. FOR ECON. COOP. & DEV., STATE OF IMPLEMENTATION OF THE OECD AI PRINCIPLES: INSIGHTS FROM NATIONAL AI POLICIES 43 (OECD Digital Economy Papers No. 311, June 2021), https://www.oecd-ilibrary.org/docserver/1cd40c44-en.pdf?expires=1636518988&id=id&accname=guest&checksum=50BA2B2E7FF6205F54DD5593F6E2DBD7.

121 ORG. FOR ECON. COOP. & DEV., RECOMMENDATION OF THE COUNCIL ON ARTIFICIAL INTELLIGENCE (May 21, 2019), https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449.

122 *See, e.g.,* U.S. GOV'T ACCOUNTABILITY OFF., ARTIFICIAL INTELLIGENCE: AN ACCOUNTABILITY FRAMEWORK FOR FEDERAL AGENCIES AND OTHER ENTITIES (June 2021), https://www.gao.gov/products/ gao-21-519sp; ADMIN. CONF. OF THE U.S., Statement #20, Agency Use of Artificial Intelligence, 86 Fed. Reg. 6616 (Jan. 22, 2021), https://www.acus.gov/research-projects/agency-use-artificial-intelligence; INDEP. HIGH-LEVEL EXPERT GRP. ON A.I., EUR. COMM'N, ETHICS GUIDELINES FOR TRUSTWORTHY AI (Apr. 8, 2019), https://op.europa.eu/en/publication-detail/-/publication/d3988569-0434-11ea-8c1f-01aa75ed71a1; GOV'T OF CAN., Directive on Automated Decision-Making (2021), https://www.tbs-sct.gc.ca/pol/doc-eng.aspx?id=32592; INT'L ORG. FOR STANDARDIZATION, Information technology—Artificial Intelligence—Overview of Trustworthiness in Artificial Intelligence, ISO/IEC TR 24028:2020 (2020), https://www.iso.org/standard/77608.html?browse=tc; U.K. COMM. ON STANDARDS IN PUB. LIFE, ARTIFICIAL INTELLIGENCE AND PUBLIC STANDARDS (Feb. 10, 2020), https://www.gov.uk/government/publications/artificial-intelligence-and-public-standards-report; ORG. FOR ECON. COOP. & DEV., State of Implementation, *supra* note 120; Carlos Ignacio Gutierrez & Gary E. Marchant, *Soft Law 2.0: Incorporating Incentives and Implementation Mechanisms into the Governance of Artificial Intelligence*, OECD: OECD.AI POL'Y OBSERVATORY (July 13, 2021); Carlos Ignacio Gutierrez & Gary E. Marchant, *A Global Perspective of Soft Law Programs for the Governance of Artificial Intelligence* (2021), https://papers.ssrn.com/sol3/ papers.cfm?abstract_id=3855171.

123 For a discussion of the pitfalls to which human decision-making can fall prey and the need to develop organizational disciplines to avoid them, see Coglianese & Lai, *supra* note 61.

124 *Id.*

125 DARRELL M. WEST & JOHN R. ALLEN, TURNING POINT: POLICYMAKING IN THE ERA OF ARTIFICIAL INTELLIGENCE 200 (2020).

artificial intelligence, and they should likewise become part of antitrust regulators' internal processes for deciding to design and deploy algorithms.[126] These processes should include documented efforts to verify that the algorithms are working as designed and to validate that they are achieving in practice the goals established for them. In setting goals and validating an algorithm's performance against these goals, government officials may find it useful to consult with members of the public to provide transparency about their plans.[127] Public engagement surrounding algorithmic design can help government officials anticipate undesirable consequences and avoid unduly narrow thinking.[128] Even when authorities use algorithmic tools for law enforcement purposes that counsel against extensive transparency and public consultation, it is still possible for officials to ensure robust internal review processes, establish expert peer reviews under confidentiality agreements, and even disclose certain general information to the public.[129]

By adhering to best practices throughout all stages of the design and deployment of algorithmic tools and systems, antitrust authorities can more likely ensure that they can reap the advantages that come from these tools and systems while also maintaining the trust of the business community and the broader public.[130] In other words, moving responsibly toward antitrust by algorithm will necessitate more than just making technological advances. It will require meeting the institutional challenges involved in building the right kind of human expertise, ethical practices, and organizational processes surrounding governmental use of artificial intelligence. Meeting these challenges should also help reduce any legal

[126] Private business already recognizes the need to think carefully about and thoroughly vet the design and development of new algorithmic tools. *See* Statement by Andrew Moore, Director of Google Cloud AI, Harnessing Transformation Technologies Symposia Series: How Artificial Intelligence and Machine Learning Transform the Human Condition (July 20, 2021), https://web.cvent.com/event/17a0dfb8-3916-4a24-b4b7-70a2b0f08804/websitePage:645d57e4-75eb-4769-b2c0-f201a0bfc6ce. For a video of Andrew Moore's remarks, see HOW ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TRANSFORM THE HUMAN CONDITION, https://www.youtube.com/watch?v=HyuqxdfC40E (last visited March 13, 2022). For discussion of methods for auditing machine-learning algorithms, see Joshua A. Kroll, Solon Barocas, Edward W. Felten, Joel R. Reidenberg, David G. Robinson, & Harlan Yu, *Accountable Algorithms*, 165 U. PA. L. REV. 633 (2017); Miles Brundage et al., *Toward Trustworthy AI Development: Mechanisms for Supporting Verifiable Claims*, ARXIV:2004.07213V2 [CS.CY] (2020); AUDITINGALGORITHMS, *Supreme Audit Insts. of Fin., Ger., the Neth., Nor., and the U.K., Auditing Machine Learning Algorithms: A White Paper for Public Auditors* (Nov. 24, 2020), https://www.auditingalgorithms.net/; Adriano Koshiyama, Emre Kazim, & Philip Treleaven, *Familiar Methods Can Help to Ensure Trustworthy AI as the Algorithm Auditing Industry Grows*, OECD: OECD.AI POL'Y OBSERVATORY (Aug. 10, 2021), https://oecd.ai/en/wonk/algorithm-auditing-trustworty-ai; Adriano Koshiyama et al., *Towards Algorithm Auditing: A Survey on Managing Legal, Ethical and Technological Risks of AI, ML and Associated Algorithms* (forthcoming), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3778998.
[127] Ellen P. Goodman, *Smart Algorithmic Change Requires a Collaborative Political Process*, REGUL. REV. (Feb. 12, 2019), https://www.theregreview.org/2019/02/12/goodman-smart-algorithmic-change-requires-collaborative-political-process/.
[128] Coglianese & Lai, *supra* note 61; *cf*. Cary Coglianese, Heather Kilmartin, & Evan Mendelson, *Transparency and Public Participation in the Federal Rulemaking Process: Recommendations for the New Administration*, 77 GEO. WASH. U. L. REV. 924, 927 (2009) ("Increased participation allows agencies to obtain information that may help them better understand how current policies could be improved and also how the public or regulated parties would respond to a change in policy. Participation can therefore help decision-makers better foresee and appreciate the impact of decisions they are contemplating."); Michael Asimow, *Nonlegislative Rulemaking and Regulatory Reform*, 1985 DUKE L.J. 381, 402–03 (1985) (noting that public engagement "broadens an agency's perspective, which otherwise might not extend beyond the views of the staff or the client groups with whom the staff regularly consults").
[129] Coglianese & Lehr, *supra* note 106.
[130] Cary Coglianese & Kat Hefter, *From Negative to Positive AI Rights*, WM. & MARY BILL RTS. J. (forthcoming).

risks that antitrust agencies may find associated with the transition to computational antitrust.

Conclusion

The digital technologies transforming private markets present daunting challenges for all regulators. But perhaps nowhere more than in the realm of antitrust do the rapid changes created by digital platforms, dynamic pricing algorithms, and other new technologies present a more direct challenge to governmental performance. Today's technological advances are leading to markets rife with possibilities for increasingly subtle and evasive forms of anticompetitive behavior by private firms. If antitrust authorities simply maintain their operational and analytic status quo, they are likely to be left behind by private sector innovation and will fail to fulfill their public mandates.

But just as technological advances present new problems for antitrust authorities, they also present potential new solutions that can assist antitrust regulators in identifying and addressing anticompetitive behavior. To implement these new machine-learning solutions with success, antitrust authorities must build up their organizational capacity to deploy algorithms effectively and responsibly. An increasing shift to the algorithmic administration of antitrust law and policy will not be easy and may pose some risk of new legal challenges. But with thoughtful design and development, along with appropriate transparency and public engagement, antitrust authorities should be able to build public confidence in, and withstand judicial scrutiny of, their use of "antitrust by algorithm."