# A GENERAL FRAMEWORK FOR ANALYZING THE EFFECTS OF ALGORITHMS ON OPTIMAL COMPETITION LAWS

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ABSTRACT

Competition laws are influenced by economic presumptions regarding how markets operate. Such presumptions generally relate to how humans interact, such as how human decision-makers – whether acting as individuals or as agents of a firm – gather information, send signals, and deal with complex, uncertain, or fast-changing market environments. The exponential growth in the use of algorithms by market participants to perform a myriad of tasks is challenging such presumptions. The lowering of access barriers to real-time data on market conditions, coupled with semi-automated decision-making by sophisticated and autonomous robo-economicus, requires us to rethink the economic presumptions embedded in our laws. Indeed, as we show, in many cases, the application of existing legal presumptions to markets in which decisions are made by sophisticated algorithms operating on big data, increase both the frequency and the harms of false negatives and, although less frequently, false positives.

Research thus far has largely focused on how algorithms affect specific types of competition rules. This article goes further, to suggest a general framework for identifying such effects. We employ decision theory to help determine how competition laws should be optimally framed in the age of algorithmic decision-making. As we show, once the use of sophisticated AI-empowered algorithms is assumed, legal presumptions with regard to some types of conduct must be changed. We suggest a typology of six different effects, ranging from no effect at all to a need for new prohibitions. Our theoretical analysis is aided by real-world examples, including cases where the introduction of sophisticated algorithms affects the choice between rules versus standards, the content of the prohibition, or procedural rules. We hope our

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meta-level analysis brings more clarity to a much-needed reboot of our regulatory framework in the age of algorithms.

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## I. INTRODUCTION

Competition laws often embed economic presumptions regarding the way markets operate. Such presumptions generally relate to how humans interact, such as how human decision-makers – whether acting as individuals or as agents of a firm – gain information, send signals, and deal with complex, uncertain, or fast-changing market environments. The exponential growth in the use of algorithms by market participants to perform a myriad of tasks is challenging these presumptions. This is because the lowering of access barriers to real-time data on market conditions, coupled with semi-automated decision-making by sophisticated and autonomous robo-economicus, often changes market dynamics. For example, algorithms may change the prevalence, effects or the conditions for different types of anti-competitive effects. Consequently, it is necessary to update our presumptions to account for the transformative impact of algorithms on competition. As this article shows, many competition rules no longer serve their purpose in a world where algorithmic decision-making is (partly) replacing human decision-making. It then identifies and exemplifies a typology of six different effects of algorithms on optimal competition laws.

The use of algorithms – especially those based on artificial intelligence (AI) – by market participants is increasing exponentially. Firms employ algorithms to perform diverse tasks, from setting price, output, and inventory levels to predicting market dynamics and regulatory moves.[1] This is not surprising, as algorithms can bring significant benefits to decision-making processes, including cost savings, speed, precision, and sophistication, thereby improving both day-to-day decisions and long-term innovation, strategy, and vision.[2] At the same time, algorithms can exacerbate both exclusionary and exploitative conduct.[3] Modern-day competitive dynamics are reshaped by this game-changing switch to algorithmic decision-making.

This new era demands a careful examination of our legal rules, to ensure they are fit for our algorithmic age. Thus far, research has mainly focused on how algorithms affect specific rules regulating anti-competitive conduct.[4] This article goes further, to suggest a general framework for identifying and analyzing the effects of algorithms on optimal competition laws. In particular, we employ Decision Theory to help determine how competition laws should be framed once the effects of algorithms on market dynamics are taken into account. As we show, some of the legal presumptions relating to firms' ability to engage in anti-competitive conduct, and incentives to do so, no longer hold true. Rather, the application of existing legal presumptions to markets where decisions are made by sophisticated algorithms operating on big data can, in many cases, increase the instances and the harms of false negatives and, albeit less frequently, false positives.

To make our case, we first examine the effects of algorithmic decision-making on market dynamics, identifying three main effects: the raising or lowering of entry barriers, the introduction of new products and services, and – most importantly for the capture of anti-competitive

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[1] *See infra* Part II.

[2] ORG. FOR ECON. CO-OPERATION & DEV. (OECD), *Algorithms and Collusion: Competition Policy in the Digital Age* 817 (Sept. 2017), https://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm (hereinafter "OECD, *Collusion*"); Michal S. Gal, *Algorithms as Illegal Agreements*, 34 BERKELEY TECH. L. J. 67 (2019) (hereinafter "Gal, *Algorithms*"); Peter Georg Picht & Anna-Katharina Leitz, *Algorithms and Competition Law – Status and Challenges* (2024), https://ssrn.com/abstract=4716705.

[3] ORG. FOR ECON. CO-OPERATION & DEV., *Algorithmic Competition* (April 2023), https://www.oecd.org/daf/competition/algorithmic-competition-2023.pdf (hereinafter: "OECD, *Algorithmic Competition*").

[4] *See, e.g.,* Michael David Coutts, *Mergers, Acquisitions and Algorithms in an Algorithmic Pricing World*, 19 J. OF COM. L. & ECON. 1 (2022); Michal S. Gal, *Limiting Algorithmic Coordination*, 38 BERKELEY TECH. L. J. 173 (2023) (hereinafter "Gal, *Limiting*").

conduct – the ability to reduce market frictions among suppliers or between suppliers and consumers (Part II). We then embed these economic effects into a Decision Theory framework (Part III) to uncover economic presumptions ingrained in competition laws. We suggest a typology of six different effects of algorithms on competition laws, ranging from no change at all to a need for a new prohibition. Each category is exemplified by several real-world examples in which the use of algorithms affects the choice between rules versus standards, the content of the prohibition, or procedural rules, such as burdens of proof (Part IV). Our aim is to create a systematic framework for recognizing the effects of the move of markets towards algorithmic decision-making on our competition laws, rather than to canvass all affected rules. We hope our theoretical meta-level analysis brings more clarity to a much-needed and quite urgent reassessment of our existing regulatory framework by enforcers and legislators.

## II. POTENTIAL EFFECTS OF ALGORITHMS ON MARKETS

Algorithms are automated decision-making processes that employ a set of rules or procedures to data inputs in order to produce data outputs.[5] They can differ in the input data they use (e.g., prices set by rivals, inventory levels), the decision-making functions they employ (e.g., predictive analytics, optimization), their level of autonomy in determining the elements of such functions (greater vs. lesser human-in-the-loop), and the goal they are programmed to achieve (e.g., maximizing profit, predicting which firms are more likely to grow).

Compare, for example, two types of algorithms programmed to set prices for a firm's products. In the first, the coder pre-determines all of its parameters ("expert algorithm"). To illustrate, a simple follow-thy-leader algorithm sets the price to equal the competitor's price. The second algorithm is fed data on market conditions, and given a general goal: "set the price (output) that maximizes profits". The algorithm establishes its pricing parameters by using a learning function that incorporates feedback on how its previous choices influenced product demand and competitor behavior. This type of algorithm is called a *learning algorithm*, because it learns from experience. It can set prices entirely autonomously, or it may be assisted by an external expert who sets some of the decisional parameters.[6]

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[5] *See, e.g.*, THOMAS H. CORMEN ET AL., INTRODUCTION TO ALGORITHMS 5 (3rd ed. 2009). This section builds upon Gal, *Limiting*, *supra* note 4.

[6] John Asker, Chaim Fershtman & Ariel Pakes, *Artificial Intelligence, Algorithm Design and Pricing*, 112 AER PAPERS & PROC. 452 (2022) (showing that human tweaking of some parameters in a learning algorithm leads to faster coordination).

In today's digital world, the use of algorithms by market players is widespread. Algorithms are commonly used to set prices in varied sectors, including online retail,[7] tourism and hospitality,[8] and petrol stations.[9] They also assist firms in a myriad of other tasks, including collecting and analyzing relevant data, and predicting market reactions to different events.[10] This is not surprising, given that algorithms generate significant advantages. By speeding the collection, organization, and analysis of data, they enable exponentially quicker decisions and reactions to changing conditions.[11] By automating decision-making or determining which types of inputs are important for a given task,[12] they save resources. By employing analytical sophistication, they make it easier to extract information from data, leading to better predictions (such as likely reactions to changes in market conditions or the optimal equilibrium in a dynamic environment).[13] Finally, algorithms are widely available, whether created in-house or externally contracted for.[14]

Given their widening use, this section explores three main ways algorithms may affect market dynamics, all of which are relevant for designing optimal competition rules: increasing/reducing entry barriers; enabling the creation of new products, services, or processes;[15] and reducing market frictions that limit anti-competitive conduct. In some cases, these effects overlap. The magnitude of these effects is case-specific and depends on a multitude of factors, such as the availability of relevant data and the degree of market concentration. As with other tools employed by market players, the effects of algorithms on

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[7] For a review of uses of pricing algorithms *see, e.g.,* Peter Seele *et al., Mapping the Ethicality of Algorithmic Pricing: A Review of Dynamic and Personalized Pricing*, 170 J BUS. ETHICS 697 (2021). *See also* OECD, *Algorithmic Competition*, supra note 3.

[8] Arnoud V. den Boer, *Dynamic Pricing and Learning: Historical Origins, Current Research, and New Directions*, 20 SURVEYS IN OPERATIONS RESEARCH AND MANAGEMENT SCI. 1 (2015); Elena Donini, *Collusion and Antitrust: The Dark Side of Pricing Algorithms* 51 (2019), https://www.associazioneantitrustitaliana.it/wp-content/uploads/2020/10/Tesi-Elena-Donini.pdf; Andrea Guizzardi, Flavio Maria Emanuele Pons & Ercolino Ranieri, *Advance Booking and Hotel Price Variability Online: Any Opportunity for Business Customers?*, 64 INT'L J. OF HOSPITALITY MANAGEMENT 85 (2017).

[9] Stephanie Assad *et al*., *Autonomous Algorithmic Collusion: Economic Research and Policy Implications*, 37 OXFORD REV. OF ECON. POL'Y 459 (2021).

[10] OECD, *Algorithmic Competition*, supra note 3; Michal S. Gal and Daniel L. Rubinfeld, *Algorithms, AI and Mergers,* 85 ANTITRUST L. J. 684 (2024).

[11] *See, e.g.,* OECD, *Collusion*, *supra* note 2, at 14-6.

[12] *See, e.g.,* Megan T. Stevenson, *Assessing risk assessment in action*, 103(1) MINNESOTA L. REV. 303 (2018).

[13] *See, e.g.*, Matthew Adam Bruckner, *The Promise and Perils of Algorithmic Lenders' Use of Big Data*, 93 CHI.-KENT L. REV. 3 (2018); Ulrich Schwalbe, *Algorithms, Machine Learning, and Collusion*, 14 J. COMPETITION L. & ECON. 568, 591 (2018).

[14] Assad et al., *supra* note 9, at 42.

[15] See, e.g., Uri Y. Hacohen, *User-Generated Data Network Effects and Market Competition Dynamics*, 34(1) FORDHAM INTELLECTUAL PROPERTY, MEDIA AND ENTERTAINMENT LAW JOURNAL 1 (2023).

individual firms' competitiveness, or their ability to engage in exclusionary or exploitative conduct, often translates into market-wide dynamics. While economic research regarding these effects is still in its infancy, identifying them is an essential first step in determining whether our competition laws are fit for purpose. Note that here, we disregard the question of whether or not the use of algorithms in the ways explored is legal – a question we address in subsequent sections.

Given that our goal is to create a systematic framework for recognizing the potential effects of algorithms, our analysis assumes the existence of several conditions that relate to the digital ecosystem and that have fueled the growth in the use of algorithms: greater availability of data (such as more accurate data on market conditions and consumer preferences);[16] cheaper and easier data collection and storage tools (such as sensors and the cloud);[17] and advances in internet connectivity which allow for cheaper and faster data transfer.[18] We also assume that all firms have access to data-based algorithms, although many of our findings also carry over to instances in which only some market players use algorithms.[19] Finally, our analysis focuses on competitive effects, leaving for future research issues such as whether the effects of algorithms in other spheres of our lives, including democracy and human autonomy, should (partially) affect competition law.[20]

### 1. *Effects on Entry and Expansion Barriers*

One of the main effects of algorithms, in numerous settings, is the lowering or the increasing of entry and expansion barriers. This can be illustrated by access to data,[21] which is widely recognized as an important input in numerous market activities.[22] Data is the raw material for the generation of information and knowledge, which enables better-informed decisions.[23] While data is essential for the operation of

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[16] As elaborated in II.1 *infra*, access to data, by itself, can be increased by algorithms.
[17] Availability of data depends on the height of entry barriers into big data markets. *See generally* Rubinfeld & Gal, *supra* note 10.
[18] In an EU study, approximately half the retailers who answered the questionnaire said they track online prices, and most of these use automatic software programs, sometimes called crawlers. *See Final Report on the E-commerce Sector Inquiry*, at 51, COM (2017) 229 final (May 10, 2017).
[19] In today's world, access to many types of algorithms is relatively easy.
[20] For some overlap with competition law, see Michal S. Gal, *Algorithmic Challenges to Autonomous Choice*, 25(1) MICHIGAN J. OF L. AND TECH. 59 (2018).
[21] *See, e.g.,* OECD, DATA-DRIVEN INNOVATION: BIG DATA FOR GROWTH AND WELL-BEING (2015), at 391–9; JACQUES CRÉMER, YVES-ALEXANDRE DE MONTJOYE & HEIKE SCHWEITZER, EUROPEAN COMM'N—COMPETITION, COMPETITION POLICY FOR THE DIGITAL ERA 73 (2019), http://ec.europa.eu/competition/publications/reports/kd0419345enn.pdf.
[22] Filippo Lancieri and Patricia Sakowski, *Competition in Digital Markets: A Review of Expert Reports*, 26 STAN. J.L. BUS. & FIN. 65 (2021).
[23] Of course, this is not always the case. *See, e.g.,* SERGEY I. NIKOLENKO, SYNTHETIC DATA FOR DEEP LEARNING 10 (2021).

algorithms, algorithms can also help firms reduce access barriers to data in any part of the data value chain:[24] they can be programmed to automatically collect and organize data; to filter out useless data; to clean and label the data in order to make it useful; to analyze it by using sophisticated tools (e.g., deep learning or generative AI) to extract more information; and to store it more cost effectively. Furthermore, algorithms can reduce the amount of data needed to perform a given function (e.g., by incorporating previous learnings), thereby reducing costs involved in data analysis or storage. Or, by generating fit-for-purpose synthetic data on which other algorithms can be trained, algorithms can reduce the need for data cleaning and storage.[25]

Data-based algorithms, in turn, can lead to better informed decisions, which in turn can generate at least four interconnected types of cost savings. First, they can reduce the direct costs of decision-making (by, e.g., removing the need for a human decision-maker). Second, they can lower the costs of inefficient decisions (e.g., storing too much inventory). Third, they can reduce risk-based costs. A recent example involves the use of an algorithm by Amazon to predict which rival shopping sites are more likely to follow its lead were it to raise its prices. In a recent complaint, the U.S. FTC claimed that the algorithm reduced Amazon's financial risk of raising a price that would not be matched, thereby generating more than a billion dollars in excess profits for Amazon alone.[26] Finally, algorithms can reduce the costs of meeting competition. To illustrate, Meta used a predictive algorithm to detect market trends and identify, at an early stage, rivals that posed a high potential threat. These predictions informed subsequent merger proposals, designed to neutralize some competitive threats at early stages.[27] Algorithms may thus reduce the costs of entry or expansion into

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[24] For such barriers see, e.g., Michal Gal and Daniel Rubinfeld, *Access Barriers to Big Data*, 59(2) ARIZONA L. REV. 339 (2017).

[25] Michal S. Gal & Orla Lynskey, *Synthetic Data: The Legal Implications of a Data Generation Revolution*, 109 IOWA L. REV 101 (2024); Ilia Sucholutsky & Matthias Schonlau, "*Less Than One"-Shot Learning: Learning N Classes From M<N Samples*, 35(11) PROCEEDINGS OF THE AAAI CONFERENCE ON ARTIFICIAL INTELLIGENCE 9739-46 (2021), arXiv:2009.08449v1 (showing that some deep learning networks can learn N new classes given only M < N examples).

[26] Case 2:23-cv-01495-JHC, *FTC v. Amazon.com Inc.*, Updated Complaint (Nov. 2, 2023), at 119.

[27] AUTORIDADE DA CONCORRENCIA, DIGITAL ECOSYSTEMS, BIG DATA AND ALGORITHMS, 87 (2019), https://www.concorrencia.pt/sites/default/files/processos/epr/Digital%20Ecosytems%2C%20Big%20Data%20and%20Algorithms%20-%20Issues%20Paper.pdf; *Federal Trade Commission v. Facebook, Inc.*, Complaint for Injunctive and Other Equitable Relief (Case No. 1:20-cv-03590. D.C. Cir.), https://www.ftc.gov/system/files/documents/cases/051_2021.01.21_revised_partially_redacted_complaint.pdf; Gal and Rubinfeld, *AI and Mergers*, *supra* note 10.

markets, both directly or indirectly (e.g., by increasing the chances of some market players to receive loans they would otherwise not be granted).[28]

The effects of a reduction of some entry or expansion barriers on competition depend, inter alia, on how widespread is access to algorithmic-generated benefits. When only a small number of firms has access to such benefits, they can gain a substantial competitive advantage, thereby raising entry barriers for others. Consider Amazon's anticipatory shipping algorithm. The algorithm analyzes the buying habits of consumers in a given geographic area, and proactively ships items they are most likely to purchase to distribution centers near them. Amazon then recommends these items to the targeted consumers.[29] Competitors who be unable to offer equally fast shipping at comparable costs on such items, face entry barriers.

Algorithms can be intentionally designed to create entry barriers. Egerton-Doyle and Ford examine how algorithms might technologically restrict rivals' access to essential datasets or platforms.[30] This can be accomplished by impeding or degrading interoperability between firms and datasets.

### 2. *Inducers of New or Better Services or Products*

Algorithms can enable market players to create new or better services or products, potentially even opening up new markets. Consider new products, such as autonomous cars. The operation of such cars is only possible because of the employment of algorithms. Firms like Waymo, Alphabet's self-driving technology division, use algorithms to create synthetic data to train their cars, collect data from the car's surroundings, analyze such data, and make immediate decisions based on such data.[31] Or consider a new service such as automatic check-out, which frees consumers from having to physically scan items for purchase at either self-service or traditional attended tills. To operate, such systems must be able to recognize all products placed in a buyer's cart from any angle, without incurring high costs. Amazon, which

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[28] See, e.g., Andreas Fuster *et al.*, *Predictably Unequal? The Effects of Machine Learning on Credit Markets*, 77(1) THE J. OF FINANCE 5 (2022) (finding that machine learning models used for credit decisions increased mortgage approval rates for minority applicants compared to traditional models).
[29] Bernard Marr, *The 10 Best Examples of How Companies Use AI in Practice* (July 2, 2021), https://bernardmarr.com/the-10-best-examples-of-how-companies-use-artificial-intelligence-in-practice/. The benefits in this example are also affected by access to other inputs, including big data and distribution facilities.
[30] Verity Egerton-Doyle & Jonathan Ford, *Algorithms, Big Data, and Merger Control, in* ALGORITHMIC ANTITRUST 87, 96-8 (Aurelien Portuese ed., 2022).
[31] Elise Devaux, *Types of Synthetic Data and 4 Examples of Real-life Applications (2022)*, STATICE (May 29, 2022), https://www.statice.ai/post/types-synthetic-data-examples-real-life-examples.

pioneered this technology, uses a computer-vision algorithm trained on algorithm-generated synthetic images to perform this task.[32]

Or consider an improvement to an existing service or product. Google Duplex uses natural language processing algorithms to create an AI voice interface that can make phone calls and schedule appointments on one's behalf, replacing human assistants.[33]

Algorithms can also open up new markets. Consider AlphaFold, an algorithm from DeepMind that succeeded in solving the decades-long puzzle of protein-folding, by accurately and efficiently predicting the 3D shape of any unknown protein using just its DNA or RNA source code.[34] The algorithm comprises a significant scientific breakthrough in the understanding and treatment of human disease,[35] potentially leading to new medicines.

### *3. Reducing Market Frictions that Limit Anti-Competitive Conduct*

Most importantly for our analysis, algorithms can reduce market frictions, defined as market conditions that limit the ability of market players to maximize their profits.[36] Examples of market frictions include imperfect information with regard to the incentives, abilities, or actions of suppliers, consumers, competitors, or regulators; transaction costs; uncertainty regarding market conditions; inability to react sufficiently fast to changing conditions; inability to create a credible signal (e.g., of quality or commitment to a certain scheme); and collective action problems.

A reduction in market frictions is often correlated with increased competition.[37] Indeed, the two preceding categories of algorithmic effects are rife with examples in which the use of algorithms by suppliers reduced market frictions, such as transaction costs or uncertainty, and led to more competition and to dynamic efficiency. Reducing frictions can, in turn, mitigate market failures and enhance allocative, productive and dynamic efficiencies that characterize well-functioning markets.

Here we explore instances where reducing frictions[38] leads to the opposite result: strengthening the ability of market players to engage in

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[32] Marr, *supra* note 29.
[33] *Ibid*.
[34] Bryan McMahon, *AI Is Ushering in a New Scientific Revolution*, GRADIENT (June 4, 2022), https://thegradient.pub/ai-scientific-revolution.
[35] *Ibid*.
[36] S*ee also* Barak Orbach, *The Friction Paradox: Intermediaries, Competition, and Efficiency*, 68(2) ANTITRUST BULLETIN 234 (2023).
[37] *See, e.g.*, DEP'T JUST. & FED. TRADE COMM'N, DRAFT MERGER GUIDELINES (2023).
[38] In some situations, algorithms can also increase frictions, potentially leading to pro- or anti-competitive effects. We leave such cases for future study.

anti-competitive conduct.[39] Such frictions can be natural or man-made, internal or external. They are direct, rather than indirect (such as when increasing entry barriers creates stronger market power).

a. Reducing Frictions to Coordination

Let us first focus on market frictions that affect the ability to set coordinated supra-competitive trade terms. A helpful way to understand the effects of algorithms on such market frictions is through the lens of the economist and Nobel laureate George Stigler's three conditions required for coordination among competitors: agreement on trade conditions, an ability to detect deviations, and a credible threat of punishment.[40] Market frictions reduce the likelihood of achieving any of the three conditions.[41]

The first condition requires reaching an agreement on the trade conditions that will profit all competitors. We discuss four sources of market friction that limit the ability of firms to reach such an agreement, all recognized in the economic literature and relied upon in case law, and show how algorithms affect them. The first focuses on the ability of competitors to calculate a joint profit-maximizing price.[42] This task is especially difficult in markets with differentiated products, or where market conditions change rapidly.[43] Algorithms can help overcome such market frictions. This can be illustrated by the *Topkins* case, in which competing sellers used an AI-powered dynamic pricing algorithm that was programmed to calculate the cartelistic price of different posters sold online at different times.[44] The algorithm's sophistication and speed made it easier, quicker, and less costly to perform the multi-dimensional analysis required to set prices at a level which would

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[39] Intermediaries such as two-sided platforms can engage in strategic market power exploitation by reducing friction in one market and increasing it in the other. Orbach, *Friction Paradox, supra* note 36, at 1; Barak Orbach, *Middlemen Forever: Competition and Opportunism in the Digital Economy*, CONCURRENCES N° 4-2021 (Nov. 2021) 30; Daniel F. Spulber, *Market Microstructure and Intermediation*, 10(3) J. ECON. PERSP. 135 (1996).

[40] George J. Stigler, *Theory of Oligopoly*, 72 J. POLITICAL ECON. 44, 44–46 (1964). The next four paragraphs build on Gal, *Algorithms, supra* note 2. A fourth condition, assumed by Stigler, is high entry barriers. Where the conduct is illegal, a fifth condition involves the ability to conceal the anti-competitive agreement from regulators, suppliers, and consumers.

[41] This discussion is largely based on Gal, *Algorithms, ibid*.

[42] Stigler, *supra* note 40.

[43] This is also echoed in the Merger Guidelines, *supra* note 37.

[44] Press Release, 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. *See also* Salil K. Mehra, *Price Discrimination-Driven Algorithmic Collusion: Platforms for Durable Cartels*, 26 STANFORD J. OF L., BUS. AND FIN. 171 (2021).

sustain coordination.[45] Importantly, not all competitors need to employ sophisticated algorithms or have strong computational power. Rather, where products and production costs are homogenous, only one competitor needs to employ a sophisticated algorithm that calculates the joint profit-maximizing price, while the rest employ a simple follow-thy-leader algorithm.

The second source of friction that may impede reaching an agreement relates to uncertainty. In many real-world situations, competitors have incomplete information about the payoffs of their actions. They learn about such payoffs via observations generated by responses to market conditions. Yet such learning might take time or might be muddled by incorrect analysis,[46] reducing firms' ability and incentive to coordinate. Algorithms can reduce such uncertainty in three main ways. First, as noted above, their sophistication reduces uncertainty about the joint profit-maximizing price. Interestingly, use of an algorithmic price recommender could, by itself, strengthen the trust of some market players that the price is set at the profit-maximizing level. This can be exemplified by the case recently brought against RealPage, provider of an algorithm that recommends to landlords rent levels designed to maximize their profits.[47] The recommendations are based on data RealPage gathers from its clients, including private information on rents charged by nearby competitors. A ProPublica investigation revealed a psychological effect of the algorithm: it strengthened the willingness of property managers to raise prices significantly and frequently, even when the steep price hikes surprised them.[48] Second, by computing various parties' expected reactions to different actions, algorithms can reduce uncertainty with regard to regulatory responses to a firm's actions. And third, for the same reason, algorithms can reduce uncertainty regarding how rivals would react to changes, including changes in one's own prices.

The role of algorithms in reducing uncertainty is multifaceted. As economic studies show, the ability to communicate price choices in

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[45] To be jointly profitable, the coordinated price need not be the perfect profit-maximizing price (i.e., the Pareto-optimal price, which is the highest price which still maximizes the firms' profits). Rather, firms may still find it profitable to coordinate so long as the price is the best approximation of the maximal price that can be set with the existing data, and is greater than the price which would have been set absent coordination.

[46] See, e.g., C. Steinhardt & E. Gomez-Villeneuve, *How do uncertainty and ambiguity influence cooperation among firms?* 168 JOURNAL OF ECONOMIC BEHAVIOR & ORGANIZATION 57 (2019).

[47] Heather Vogel, *Department of Justice Opens Investigation into Real Estate Tech Company Accused of Collusion with Landlords*, PROPUBLICA, Nov. 23, 2022, https://www.propublica.org/article/yieldstar-realpage-rent-doj-investigation-antitrust; Joseph E. Harrington, *Party Pricing Algorithms for Competition Law, forthcoming*, THEORETICAL INQUIRIES IN LAW (2024).

[48] Heather Vogel, *Rent Going Up? One Company's Algorithm Could Be Why*, PROPUBLICA, Oct. 15, 2022, https://www.propublica.org/article/yieldstar-rent-increase-realpage-rent.

oligopolistic markets affects the ability to coordinate.[49] An algorithm is a "recipe" for making decisions.[50] Other algorithms can be instructed to "understand" its internal logic.[51] This is a central difference between human and algorithmic coordination.[52] While a human cannot read the mind of another and predict that person's future actions, when an algorithm is transparent to others, a coder or another algorithm can accurately predict its future actions when given any specific sets of inputs (including reactions to other players' actions). Importantly, for this to be true, the algorithm need not be directly observable. Rather, its decision processes can be indirectly observed, provided that sufficient information exists about its decisions under changing market conditions.[53] Furthermore, employing a certain type of algorithm can send a strong and clear signal to other market players about the decisional parameters used to set trade conditions, the frequency of searches for deviations, and the punishment for deviation.[54] The algorithm thus creates both pre-agreement communication that the other party can "read" and understand, and a self-commitment device. This finding cannot be overstated: the mere (direct or indirect) observation of the algorithm by competitors may, by itself, serve to facilitate coordination. The algorithm communicates much more than price choices: it communicates a business strategy. Such communications need not be binding, but algorithms may strengthen this aspect as well.

The third source of friction that may impede agreement among competitors on trade conditions relates to personality traits. Algorithms are devoid of ego or emotions, and therefore are immune to things like long-simmering anger. This makes their decisions more logical and predictable, thereby lowering barriers to agreement.[55] Finally, the fourth source is the risk that the conduct will be illegal. The use of algorithms limits the need for some forms of communication (e.g., verbal assurances of commitment or advance price change announcements)

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[49] *See* Christoph Engel, *Tacit Collusion: The Neglected Experimental Evidence*, 12 J. EMPIRICAL LEGAL STUD. 537 (2015).
[50] Gal, *Algorithms, supra* note 2.
[51] Even if different computer languages are used, an algorithm can "translate" the code.
[52] Gal, *Algorithms, supra* note 2; Emilio Calvano, Giacomo Calzolari, Vincenzo Denicolò, Joseph E. Harrington Jr. & Sergio Pastorello, *Policy Forum: Protecting Consumers From Collusive Prices Due to AI*, 370 SCIENCE 1040 (2020).
[53] Bruno Salcedo, Pricing Algorithms and Tacit Collusion 3 (Nov. 1, 2015) (unpublished manuscript) (on file with author).
[54] *See, e.g.*, Zach Y. Brown & Alexander MacKay, *Competition in Pricing Algorithms* 1 (Harv. Bus. Sch., Working Paper No. 20-067, 2020) (finding that prices for over-the-counter medications rose when firms set their pricing algorithms to update prices at different frequencies. The firm with the least frequent updates acted as price leader).
[55] Gal, *Algorithms, supra* note 2.

that were seen as necessary for establishing cooperation in a world based on human coordination.[56]

Stigler's second condition requires that coordinators be able to detect deviations from the supra-competitive equilibrium.[57] Since each firm has an incentive to cheat in order to increase its own profit, coordination is less stable to the degree that market frictions weaken the ability of other firms to completely or swiftly detect such deviations. Green and Porter showed that where demand fluctuations are significant and difficult to distinguish from deviations from the equilibrium, coordination is difficult to achieve.[58] Algorithms can reduce such frictions. First, they reduce the costs of surveillance. Second, they may better differentiate between deviations aimed at increasing personal profit, on the one hand, and natural reactions to changes in market conditions, or even errors, on the other. They may thereby prevent misguided price wars.[59] Furthermore, algorithms may reduce firms' incentives to deviate in the first place. [60] If an algorithm can react almost immediately to changes in rivals' online prices, and transactions are small and frequent, price reductions can be immediately detected and matched, making them unprofitable to begin with.[61] Similar effects also limit the incentives of third parties to employ maverick algorithms in order to skim the coordinated price.

The third condition requires that firms must be able to create a credible threat of retaliation to discourage deviations.[62] Once again, market frictions may limit the degree to which that condition is met. For example, firms may miscalculate the level of efficient sanction. Algorithms can better calculate the level of sanctions necessary to discourage deviations. Further frictions can arise if firms cannot create a credible threat of retaliation. Algorithms can reduce such frictions if their decision mechanisms automatically trigger a price war upon observing a deviation, and changing such mechanism is not simple or takes a long time relative to the frequency of market transactions.[63]

The reductions in market frictions described here may lead, inter alia, to autonomous coordination, not based on prior agreement. Under this scenario, the algorithm is given a goal (e.g., profit maximization), and autonomously determines its own pricing strategies. A growing

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[56] William E. Kovacic, Robert C. Marshall, Leslie M. Marx & Halbert L. White, Jr., *Plus Factors and Agreement in Antitrust Law*, 110 MICH. L. REV. 393, 417 (2011).
[57] Stigler, *supra* note 40, at 46.
[58]. *See* Edward J. Green & Robert H. Porter, *Noncooperative Collusion Under Imperfect Price Information*, 52 ECONOMETRICA 87 (1984).
[59] OECD, *Collusion*, *supra* note 2, at 22.
[60] Gal, *Algorithms, supra* note 2.
[61] Antonio Capobianco & Pedro Gonzaga, *Algorithms and Competition: Friends or Foes*?, COMP. POL. INT'L 2 (August 2017); OECD, *Collusion, supra* note 2, at 23-24.
[62] *Id*.
[63] Gal, *Algorithms, supra* note 2.

consensus exists that AI-powered pricing algorithms can make it easier for competitors to coordinate and sustain increased prices in markets where market frictions previously made coordination much more difficult. This consensus is based on theoretical,[64] experimental, and empirical studies. For example, recent experimental studies using computer simulation have revealed the emergence of autonomous algorithmic coordination under some market conditions, suggesting that conscious parallelism by pricing algorithms is a real possibility.[65] Coordination arose with no human intervention,[66] and the algorithmic strategy was not conditioned on rivals' commitment to stick to the supra-competitive equilibrium, nor did it involve direct communication beyond reacting to rivals' prices.[67] Empirical evidence showing that algorithms can learn to coordinate in practice is also beginning to accumulate.[68] Assad, Clark, Ershov, and Xu found that prices in the German retail gasoline market rose substantially (9–28%) due to parallel conduct after both firms in a duopoly situation switched from manual to algorithmic pricing.[69] Mussolff found that pricing algorithms used by third-party sellers on Amazon Marketplace effectively coaxed competitors to raise their prices by alternating infrequent large price increases with periods of

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[64] *See, e.g.,* EZRACHI & STUCKE, VIRTUAL COMPETITION: THE PROMISE AND PERILS OF THE ALGORITHM-DRIVEN ECONOMY (2016); Salil K. Mehra, *Antitrust and the Robo-Seller: Competition in the Time of Algorithms*, 100 MINNESOTA L. REV. 1323 (2016) Gal, *Algorithms*, *supra* note 2; ALGORITHMS, COLLUSION AND COMPETITION LAW (Steven Van Utysel, Salil K. Mehra, & Yoshiteru Uemura eds., 2023).

[65] *See, e.g.,* Emilio Calvano, Giacomo Calzolari, Vincenzo Denicolò, & Sergio Pastorello, *Artificial Intelligence, Algorithmic Pricing, and Collusion*, 110 AM. ECON. REV. 3267 (2020). Banchio and Mantegazza provide theoretical underpinnings for algorithmic collusion between Q learning algorithms. Banchio and Mantegazza, *Artificial Intelligence and Spontaneous Collusion* (Feb. 12, 2022), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4032999. For work on prediction algorithms *see, e.g.,* Jeanine Miklós-Thal & Catherine Tucker, *Collusion by Algorithm: Does Better Demand Prediction Facilitate Coordination Between Sellers?* 65 MANAGEMENT SCI. 1552 (2019). For a mathematical definition of algorithmic coordination *see* Arnoud V. den Boer, *A (Mathematical) Definition of Algorithmic Collusion* (November 17, 2023), https://ssrn.com/abstract=4636488.

[66] In a follow-up study, Calvano et al. also show that algorithmic collusion can cope with more complex economic environments with imperfect information and imperfect monitoring. Emilio Calvano et al., *Algorithmic Collusion with Imperfect Monitoring*, 79 INT'L J. INDUS. ORG. 79 (2021). A recent study with generative AI large language models found that such algorithms learned to coordinate prices in a few hundred iterations, much faster than Q learning algorithms. Sara Fish, Yannai A. Gonczarowski, Ran Shorrer, *Algorithmic Collusion by Large Language Models* (2024), https://arxiv.org/pdf/2404.00806.

[67] *Id*. For critiques of interpretations that see the results as coordination in the economic sense, *see, e.g.*, Arnoud V. den Boer, Janusz M. Meylahn, Maarten Pieter Schinkel, *Artificial Collusion: Examining Supracompetitive Pricing by Q-learning Algorithms* (2022) https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4213600, and papers cited therein, at 4.

[68] Assad *et al*., *supra* note 9, at 5.

[69] *Id.* at 31.

frequent, stable, and small price decreases, leading to a median price increase of 8%.[70]

Furthermore, algorithms can assist in facilitating coordination even when entry barriers are not otherwise sufficiently high to prevent potential entry. For example, the algorithm can help set the coordinated price at a level which deters entry. While this price may be lower than the monopoly price, it might still be above that which would have been set absent such deterrence. Alternatively, algorithms might make it easier and more profitable for entrants to join the coordination.[71] While both strategies are, of course, also possible without the use of algorithms, the speed and sophistication of algorithms make such strategies easier to engage in, especially if the potential entrant also uses an algorithm.

Of course, algorithms cannot help satisfy Stigler's conditions in all markets.[72] Nonetheless, at least in some circumstances, algorithms may both motivate coordination and increase its stability.[73]

#### b. Reducing Frictions that Constrain Abuse of Dominance

Let us now explore how algorithms can reduce market frictions that constrain unilateral anti-competitive conduct.

Consider an informational market friction that limits the ability of a dominant firm to calculate each consumer's demand elasticity (Willingness To Pay: WTP). The more precisely a dominant firm can estimate WTP, the more effectively it can price its products to capture the maximum potential surplus from each individual consumer.[74] Economists often emphasize the difficulty of calculating WTP, as it requires

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[70] Leon Mussolff, *Algorithmic Pricing Facilitates Tacit Collusion: Evidence from E-Commerce*, EC'22: PROCEEDINGS OF THE 23RD ACM CONFERENCE ON ECONOMICS AND COMPUTATION 32 (2022); Leon Mussolff, *Algorithmic Pricing, Price Wars and Tacit Collusion: Evidence from E-Commerce* (2024), https://lmusolff.github.io/papers/Algorithmic_Pricing.pdf. While use of these strategies is still low, they are growing in popularity. Amazon was not part of any such scheme.

[71] This possibility weakens the justification for legal rules that require proof of limited potential entry into the market in order to find potential for coordination in the market. *See, e.g.*, Case T-342/99, Airtours plc v Commission [2002] ECR II-2585

[72] Ashwin Ittoo & Nicolas Petit, *Algorithmic Pricing Agents and Tacit Collusion- A Technological Perspective*, *in* L'INTELLIGENCE ARTIFICIELLE ET LE DROIT (Hervé Jacquemin & Alexandre de Streel eds., 2017), at 11–12.

[73] *See also* OECD, *Collusion, supra* note 2, at 35 ("Algorithms might affect some characteristics of digital markets to such an extent that tacit collusion could become sustainable in a wider range of circumstances possibly expanding the oligopoly problem to non-oligopolistic market structures").

[74] *See, e.g.,* 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, 406-407 (2020).

predicting how each consumer will react under different, potentially dynamic market conditions.[75]

Algorithms provide a more efficient mechanism to calculate WTP.[76] First, they reduce some access barriers to relevant data. Second, their speed and sophistication allow them to analyze a large number of factors simultaneously over a very large dataset, increasing firms' ability to swiftly and profitably mine big data for indicators of consumers' WTP. This, in turn, enables firms to identify narrower consumer segments in which competition has more limited effects, thus enabling better discrimination between consumers with low switching costs (marginal consumers) and those with high switching costs (inframarginal consumers).[77]

Algorithms could also increase firms' ability to engage in data-based discrimination based on such WTP calculations.[78] This is because algorithms enable firms to more quickly and efficiently adjust prices closer to their profit-maximizing level in dynamic settings. Employing algorithms may thus enable some firms to profitably engage in first-degree price discrimination,[79] and others to engage in third-degree price discrimination by identifying narrower consumer segments in which competition has more limited effects.[80] Furthermore, while discriminatory pricing has traditionally been largely restricted to the wholesale level, platforms that connect suppliers directly and cheaply with individual consumers make it easier to use targeted pricing at the retail level.[81] While price discrimination can increase output, in some circumstances it can also create significant exclusionary and exploitative effects.[82]

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[75] *See, e.g.*, Jonas Schmidt & Tammo H. A. Bijmolt, *Accurately measuring willingness to pay for consumer goods: a meta-analysis of the hypothetical bias*, 48 J. OF THE ACADEMY OF MARKETING SCIENCE 499 (2020) (meta-analysis of studies highlighting the difficulty of obtaining accurate WTP).

[76] *See, e.g.*, Peter Seele, Claus Dierksmeier, Reto Hofstetter & Mario D. Schultz, *Mapping the Ethicality of Algorithmic Pricing: A Review of Dynamic and Personalized Pricing*, 170 J. BUS. ETHICS 697, 702 (2019).

[77] Sheng Li, Claire Chunying Xie & Claire Feyler, *Algorithms & Antitrust: An Overview of EU and National Case Law*, 102334 CONCURRENCES 3 (2021).

[78] EZRACHI & STUCKE, *supra* note 64, at 101. In 2016 the U.S. antitrust authorities recognized the possibility that "[g]iven sufficient data, firms could model and predict differences in consumers' WTP, thereby making price discrimination more feasible." Yet data imperfections might lead to practical limitations. Note, *supra* note 82, at 2; David J. Teece, *Big Tech and Strategic Management: How Management Scholars Can Inform Competition Policy*, 37 ACADEMY OF MANAGEMENT PERSPECTIVES 1, 2 (2023).

[79] Of course, the use of these algorithms can also lower prices in some cases, depending on the circumstances.

[80] *See, e.g.*, Li, Xie & Feyler, *supra* note 77.

[81] Thomas K. Cheng & Julian Nowag, *Algorithmic Predation and Exclusion*, 25(1) U. PENN.. J. BUSS. L. 41 (2023).

[82] United States, Note to OECD, *Price Discrimination*, DAF/COMP/WD(2016)69, at 3, https://www.ftc.gov/system/files/attachments/us-submissions-oecd-2010-present-other-international-competition-fora/price_discrimination_united_states.pdf.

This increased ability to determine WTP and to engage in discrimination affects economic predictions regarding the potential for different types of anti-competitive conduct.[83] To illustrate, consider a predatory pricing scheme, in which the predator charges a price below some measure of its incremental cost of production, with the expectation that its less resilient competitor will not be able to sustain losses and will exit or choose not to enter the market. Once this happens, the predator increases its price to a supra-competitive level in the expectation of recovering its accumulated losses. Chicago School economists famously argued that predation is irrational, given that it is nearly impossible for predators to fully recoup the losses suffered.[84] Their view is based on three cumulative assumptions: price discrimination is not possible, so the predator cannot separate inframarginal and marginal consumers; the predator must have sufficient capacity to be able to supply the entire market at the predatory price, including the increased demand due to the lower price; and entry barriers are low, so that once the monopolist raises its price a competitor can profitably reenter the market.[85]

Leslie,[86] as well as Cheng and Nowag,[87] show that algorithms challenge this view and increase the potential for predatory pricing.[88] This is because algorithms can enable the predator to engage in price discrimination, distinguishing between marginal and infra-marginal consumers.[89] If the firm can successfully prevent cross-sales between the two groups, only the former need to be offered low prices. Furthermore, by enabling such separation, algorithms reduce predation costs and help firms finance their predatory actions by allowing them to maintain a profit-maximizing pricing scheme for inframarginal consumers.[90] Selective price cuts also partially overcome the capacity condition, given that the seller need not supply the entire market. Finally, reentry in

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[83] Our discussion here relies on Gal and Rubinfeld, *AI and Mergers*, *supra* note 10.

[84] John S. McGee, *Predatory Price Cutting: The Standard Oil (N.J.) Case*, 1 J. L. & ECON. 137, 140 (1958) ("If I am selling 90 percent of all petroleum, a particular competitor is selling 1 percent, and we both sell at the same price and have the same average cost, I lose $90 for every $1 he loses.") Losses would be even higher under a predatory price, given that demand would be greater.

[85] Christopher Leslie, *Predatory Pricing Algorithms*, 97 NYU L. REV. (2023).

[86] *Id*.

[87] Cheng & Nowag, *supra* note 81.

[88] Leslie, *supra* note 85; Nowag & Cheng, *id*.

[89] The fact that price discrimination can reduce the costs of predation is also recognized by competition authorities. *See, e.g*., EU guidance on Article 102 (2008), section 71 ("It may be easier for the dominant undertaking to predate if it selectively targets specific customers with low prices, as this will limit the losses incurred by the dominant undertaking").

[90] Nowag & Cheng, *id.*; COMPETITION AND MARKETS AUTHORITY, ALGORITHMS: HOW THEY CAN REDUCE COMPETITION AND HARM CONSUMERS 8-10 (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.

digital markets may be affected by factors such as network effects and consumer behavioral limitations.[91]

Post-Chicago economic scholarship applies game theory models to determine how information asymmetries affect whether and how predation may lead a potential entrant to reconsider his decision to enter the market.[92] Information asymmetries can relate, inter alia, to existing market conditions such as demand elasticity, or the costs and rationality of the predator. Predation can distort market signals about profitability, leaving the entrant uncertain as to whether the lower prices set by the predator result from a decrease in demand and, if so, whether this is permanent. This uncertainty influences the expectations of potential entrants, as well as their external funders, in a way which might deter otherwise profitable entry.[93] Generally, the wider the information asymmetry, the greater the uncertainty – and the more credible the predatory action.

Within this post-Chicago predation scholarship, one of the most oft-discussed theories – and that with perhaps the greatest impact on enforcement in practice in the EU – concerns financial predation.[94] This theory holds that where the absence of a credit history means that startups might not have easy access to capital markets, predators can manipulate the perceived creditworthiness of such targets by engaging in predatory price wars that force them to cut their prices and lower their profitability.[95] To the extent that lenders then downgrade the targets' credit ratings, this strategy reduces their ability to (re)invest, and may even force them to exit the market for lack of funding.

Algorithms can affect such information asymmetries in several ways. On the one hand, their sophistication can be used by incumbents to set the predatory price at a level which best increases uncertainty, making it more difficult for outside investors to interpret the causes of their borrowers' low profits, and deterring (re)entry. On the other hand, the same trait might make it easier for entrants, using algorithms, to determine whether the lowering of prices is part of a predatory strategy.

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[91] Leslie, *supra* note 85; Nowag & Cheng, *id*.

[92] *See, e.g.,* Patrick Bolton, Joseph F. Brodley and Michael H. Riordan, *Predatory Pricing: Strategic Theory and Legal policy*, 88 GEORGETOWN L. J. 2239 (2000). Some jurisdictions have already put this into practice. *See, e.g.,* EU COMMISSION, GUIDANCE ON THE COMMISSION'S ENFORCEMENT PRIORITIES IN APPLYING ARTICLE 82 OF THE EC TREATY TO ABUSIVE EXCLUSIONARY CONDUCT BY DOMINANT UNDERTAKINGS, OJ C 45, 24.2.2009, 7, para. 67. Additional lines of research point to other causes of profitability. *See, e.g.,* Paul Milgrom and John Roberts, *Predation, Reputation, and Entry Deterrence* 27(2) J. OF ECONOMIC THEORY 280 (1982) (otherwise unprofitable predation can still be profitable and rational if it creates a reputation for predatory conduct that will likely affect multiple markets and/or successive periods of possible entry).

[93] Bolton, Brodley and Riordan, *ibid.*

[94] EU Commission, Case AT.39711 - Qualcomm (Predation) (July 18, 2019) https://ec.europa.eu/competition/elojade/isef/case_details.cfm?proc_code=1_39711

[95] Patrick Bolton and David S. Scharfstein, *A Theory of Predation Based on Agency Problems in Financial Contracting*, 80(1) AMERICAN ECONOMIC REVIEW 93 (1990).

For example, they may reduce the asymmetries of information in credit markets that make financial predation possible in the first place. We argue that a reduction in information asymmetry may also arise when we take the claim made by Leslie[96] and by Cheng and Nowag[97] one step further. As they argue, algorithms potentially increase the profitability of predation by enabling better price discrimination and the targeting of only inframarginal consumers. Yet the same action can also reduce information asymmetries for potential entrants, as it signals that the lower prices are not a result of a market-wide reduction in demand.

These examples also demonstrate that while reductions in market frictions are generally perceived in antitrust analysis to be pro-competitive,[98] their welfare effects are more complex.[99]

To sum Part II, while economic studies of how algorithms affect anti-competitive conduct are in their infancy, it is already clear that the use of algorithms can change market dynamics. Many effects are pro-competitive – reducing entry barriers and spurring competition and innovation. Yet some algorithmic uses intensify anti-competitive effects. In some scenarios, the same algorithm can create both positive and negative competitive effects. The magnitude of these effects varies widely, from negligible to transformative. Consequently, algorithmic usage may shift the relative plausibility of pro-competitive justifications and anti-competitive harm theories.

## III. Algorithms and Decision Theory

Former U.S. FTC Commissioner Maureen Ohlhausen suggested that if the word "algorithm" can be replaced by the phrase "a guy named Bob," then the algorithm's conduct should be treated in the same way as Bob's.[100] We argue that the converse is not always true. Rather, in some cases the same conduct engaged in by an algorithm and a human can have significantly different competitive effects, which might justify different legal treatment. To make this case, we first introduce decision theory, which provides a useful framework for analyzing how changes in economic presumptions regarding market dynamics should affect

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[96] Leslie, *supra* note 85.
[97] Cheng and Nowag, *supra* note 87.
[98] Orbach, *supra* note 36, at 12.
[99] Some scholarship has focused on the complex effects of market frictions in markets with two-sided intermediaries that engage in strategic market power exploitation by reducing friction in one market and increasing it in the other. Orbach, *supra* note 36, at 1; Barak Orbach, *Middlemen Forever: Competition and Opportunism in the Digital Economy,* CONCURRENCES N° 4-2021 (Nov. 2021), at 30; Daniel F. Spulber, *Market Microstructure and Intermediation*, 10(3) J. ECON. PERSP. 135 (1996).
[100] 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 Conference, May 23, 2017).

legal rules (sub-section 1). Before delving into some examples (Part IV), we suggest several general principles for the application of competition laws to algorithms (sub-section 2).

### 1. *Decision Theory, Legal Presumptions, and Standards of Proof*

Decision theory applies statistical analysis[101] to the shaping of legal rules.[102] It considers not only the presumed effects of the conduct under consideration on the interests we wish to protect, but also the costs of applying the legal rule in practice. Such costs, in turn, affect the ability and motivation of decision-makers – enforcers as well as market players, who choose between possible actions while taking into account the relevant legal rules – to achieve the law's goals.

Decision theory recognizes that decisions are often made with imperfect information, as the task of obtaining all relevant information may be too expensive, too time-consuming, or simply impossible.[103] In the present context, relevant information can relate, for example, to market conditions and the economic effects and expected reactions of market players and regulators to different decisions. Imperfect information can lead to two types of errors: false positives (type I errors), where permissible conduct is incorrectly condemned, and false negatives (type II errors), where impermissible conduct is incorrectly permitted.[104] Decision theory thus strives to discover the rules that will best achieve the law's goals while balancing an assumed level of error resulting from imperfect information against the costs of obtaining

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[101] As stated by Steve Salop, "Decision theory provides a formal methodology for rational decision-making when information is imperfect. This methodology can be described as a rational process in which a decision-maker begins with some initial, rationally-based beliefs about the possible effects of a decision. As a formal matter, those initial beliefs can be seen as a set of probabilities of potential alternative outcomes. The decision-maker bases the initial beliefs on prior knowledge and then gathers additional information to refine and improve upon those initial beliefs in order to 'update' the presumption to create revised beliefs." Steven C. Salop, *An Enquiry Meet for the Case: Decision Theory, Presumptions, and Evidentiary Burdens in Formulating Antitrust Legal Standards* (2017), https://ssrn.com/abstract=3068157 (hereinafter: "Salop, *Enquiry*"). Bayesian statistical methods use Bayes' theorem to update beliefs after obtaining new data.

[102] It was first suggested by Isaac Ehrlich & Richard A. Posner, *An Economic Analysis of Legal Rulemaking*, 3 J. LEGAL STUD. 257 (1974). For the application of Decision Theory in antitrust *see, e.g.*, C. Frederick Beckner III & Steven C. Salop, *Decision Theory and Antitrust Rules*, 67 ANTITRUST L.J. 41 (1999); Steven C. Salop, *The Evolution and Vitality of Merger Presumptions: A Decision-Theoretic Approach*, 80 ANTITRUST L.J. 269 (2015); Mark S. Popofsky, *Defining Exclusionary Conduct: Section 2, the Rule of Reason, and the Unifying Principle Underlying Antitrust Rules*, 73 ANTITRUST L.J. 235 (2006); Salop, *Enquiry*, *ibid.*

[103] Salop, *Enquiry*, *id*., at 33.

[104] *Id*; Jonathan B. Baker, *Taking the Error Out of "Error Cost" Analysis: What's Wrong with Antitrust's Right* (2015) 80 ANTITRUST L.J 1.

more information.[105] As such, it provides a helpful tool for understanding and designing both substantive and procedural legal rules.

Take, for example, legal presumptions. Such presumptions are designed to deal with the fact that legal decisions are often made with imperfect information.[106] Absent perfect information, some error costs are expected. Decision theory can determine under what conditions legal presumptions are warranted, the strength of such presumptions, and the type and verity of information that must be brought to challenge them. In the extreme case, where information costs exceed error costs, presumptions are considered irrebuttable, meaning that they are not allowed to be challenged on the basis of any new information.

Decision theory is especially relevant for evaluating existing competition laws, given that legal rules are based on economic assumptions of varying strengths about how markets operate and the likely competitive impact of a conduct under different market conditions.[107] For the purpose of this article, we assume that the main goal of competition law is to maximize long-term consumer welfare by protecting competition on the merits, while recognizing that this goal is subject to debate.[108]

In a companion paper we formalize the process by which a regulatory decision-maker should set legal rules if the aim is to maximize (long-run) consumer welfare by minimizing the expected cost of error. We show that, for any given practice, she should adopt (i) a *presumption of illegality* when the anti-competitive theory of harm associated with the practice is sufficiently more plausible than the pro-competitive justification, given precedent and state-of-the-art economic theory and evidence; (ii) a *presumption of legality* when the pro-competitive justification is sufficiently more plausible than the anti-competitive theory of harm; and (iii) no presumption (or a *neutral presumption*) when both the pro-competitive justification and the anti-competitive theory of harm are similarly plausible.

Such presumptions should optimally be *irrebuttable* when the cost of gathering and assessing the case-specific evidence that could be used to rebut the presumption exceed the expected costs of false positive errors (for a presumption of illegality) or false negative errors (for a presumption of legality).[109] Otherwise, it is optimal to allow the defendant

[105] Salop, *Enquiry*, *ibid*.
[106] I*d*.
[107] *id*.
[108] *See, e.g.*, Tim Wu, *After Consumer Welfare, Now What? The 'Protection of Competition' Standard in Practic*e, COMPETITION POLICY INT'L (April 2018); Lina M. Khan, *The New Brandeis Movement: America's Antimonopoly Debate*, 9(3) J. OF EUROPEAN COMPETITION LAW & PRACTICE 131 (2018); Herbert J. Hovenkamp, *Is Antitrust's Consumer Welfare Principle Imperiled?* 45(1) J. OF CORPORATION L. 101 (2019).
[109] We acknowledge additional potential effects that are not taken into account in this simplified model. For example, Hovenkamp and Salop argue that if it is relatively less expensive or

(where there is a presumption of illegality) or the complainant/regulator (where there is a presumption of legality) to produce relevant case-specific evidence and attempt to show that the presumption is unjustified.

Successfully rebutting a presumption of illegality ought to require showing that the pro-competitive justification fits those case-specific facts better than a sound anti-competitive theory of harm. The threshold of persuasion (how much better the fit needs to be) depends on the strength of the presumption (which itself depends, inter alia, on the level of relevant accumulated knowledge and experience with similar cases), as well as the relative costs of false positive and false negative errors.[110] The stronger the presumption and the higher the cost of the false negative error relative to that of the false positive error, the more difficult for the defendant to discharge her burden of persuasion.

Likewise, to successfully rebut a presumption of legality, the complainant or regulator should be required to show that the anti-competitive theory of harm fits those case-specific facts better than the anti-competitive justification. Again, the threshold of persuasion depends on the strength of the presumption as well as the relative costs of the two types of errors. The stronger the presumption and the higher the cost of the false positive error relative to the cost of the false negative error, the more difficult to discharge the burden of persuasion.

In short, the more certain the presumed anti-competitive effects, the higher the evidentiary burden (i.e., the higher the standard of proof) placed on the defendant to rebut a legal presumption, and vice versa.[111] This framework allows us to assess when and how competition laws should be modified in situations where algorithms are used by market participants to make decisions. We leave for future research the discussion of who is liable – whether the coder of the algorithm, the user, or even the algorithm itself.[112] We also leave for future research the

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difficult for one of the litigants to obtain the additional evidence, or if that litigant has higher stakes, its relatively higher incentive to produce favorable evidence might skew the outcome away from the merits to the advantage of that litigant. Erik Hovenkamp and Steven C. Salop, *Litigation with Inalienable Judgments*, 52 J. LEGAL STUD. 1-50 (2023). Such evidence can create bad law, which might become part of the accumulated knowledge affecting future conduct and cases, thereby increasing the typical error costs in relatively similar cases. Interestingly, irrebuttable presumptions limit such effects. In addition, compliance incentives decrease when the probability of error of either type increases. For example, a legal system with high false negatives will lead to high violation rates, because firms will not strongly fear getting caught. Steven C. Salop, *Merger Settlement and Enforcement Policy for Optimal Deterrence and Maximum Welfare*, 81 FORDHAM L. REV. 2647, 2668–69, 2669 (2013), expanding Richard A. Posner, *An Economic Approach to the Law of Evidence,* 51 STAN. L. REV. 1477, 1484 (1999). Furthermore, certain types of evidence might be more subject to misinterpretation by the fact-finder, in which case errors will be more likely. Steven C. Salop, *The Appropriate Decision Standard for Section 7 Cases*, 53(1) U. OF BALTIMORE L. REV. 453, 467 (2024).

[110] Salop, *Section 7, ibid.*

[111] Salop, *Enquiry*, *supra* note 101.

[112] For articles attempting to deal with such issues, *see, e.g.,* Gal, *Algorithms, supra* note 2.

addition of another layer of complexity that might affect the determination of an optimal legal rule: agency costs that affect the motivation of decision-makers to reach correct decisions, even when information costs are low.[113]

### *2. General Guidelines for Applying Decision Theory When Algorithms Are Used by Market Participants*

Some of the legal presumptions incorporated in competition law have already been challenged, and some have already been changed. Algorithms strengthen this need, further challenging ingrained presumptions regarding the competitive effects of different types of conduct under given market conditions, the magnitude of information costs required to correctly analyze such effects, and the extent of resultant error costs.

Some rules are equally suited to regulate humans and algorithms. Yet in numerous scenarios the use of algorithms affects the optimal balance between information and error costs. It follows that the use of algorithms may challenge the optimal balance between false positive and false negative errors and information costs on which some current legal rules are based. Thus, the legal rules (e.g., presumptions of legality or illegality), their per se or rebuttable character, as well as the standards of proof or thresholds of persuasion used for such rebuttals, may have to change in markets where algorithms are used in commercial strategies.

Algorithms can affect error costs. For example, by increasing the likelihood of anti-competitive conduct, algorithms that reduce market frictions lead to more false negatives. This would then require changes in legal rules influenced by the Chicago School's focus on minimizing false positive errors over false negatives.[114] This focus is based on two main assumptions. First, the enforcement limitations affecting courts, in particular their limited ability to differentiate between pro- and anti-competitive conduct in complex situations, lead to frequent errors, both false positives and false negatives.[115] Second, non-intervention is preferable and will often result in low false negative error costs, given that most types of anti-competitive conduct will be restrained by market forces, whereas neither the market nor the legal process are likely to redress to the he costs of pretrial false positives.[116] To illustrate, it was

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[113] *See, e.g.,* George J. Stigler, *The Theory of Economic Regulation*, 2(1) THE BELL J. OF ECONOMICS AND MANAGEMENT SCIENCE 3 (1971).
[114] Baker, *supra* note 104.
[115] *Ibid*., at 29-32. This can be exemplified by reluctance to regulate high prices, as such. *See, e.g.,* Michal S. Gal, *Monopoly Pricing as an Antitrust Offense in the U.S. and the EC: Two Systems of Belief about Monopoly?*, 49 ANTITRUST BULLETIN 343 (2004).
[116] *See, e.g.,* ROBERT H. BORK, THE ANTITRUST PARADOX: A POLICY AT WAR WITH ITSELF (1978).

assumed that oligopolistic coordination is inherently unstable, and that markets thus tend to self-correct.[117] As Baker argues, these Chicago-School assumptions "systematically overstate the incidence and significance of false positives, understate the incidence and significance of false negatives, and understate the net benefits of various rules by overstating their costs."[118] Yet many rules are still based on such assumptions.[119]

The advent of algorithms, and the changes in market dynamics that they cause, further undermine these assumptions. As observed above, the speed and sophistication of algorithms implies that they can achieve anti-competitive results under a broader set of circumstances relative to humans. Furthermore, their use can strengthen the consequences of exclusionary or exploitative conduct. Accordingly, **the Chicago School focus on limiting false positives might not create the right balance** in many instances of algorithmic interactions. Rather, the application to algorithms of competition laws designed for human interactions, and based on a strong belief in the self-correcting powers of markets, will **increase the likelihood and the resultant costs of false negative errors** where algorithms increase the incidence and significance of anti-competitive conduct.

Algorithms also affect information costs. The discussion above suggested instances in which algorithms affect the information costs of market players.[120] In addition, they can affect enforcers' information costs. The use of algorithms by market participants, especially if they are transparent, may increase enforcers' clarity on how decisions were made, and how firms (will) react to different market conditions, thereby overcoming some evidentiary difficulties.[121] This is because algorithms are "recipes for action,"[122] a fact which makes it easier to anticipate their actions, relative to humans.[123] By inspecting the code, testing it with different datasets, determining how the alteration of a certain feature affects its outcome, and applying techniques to increase the

[117] Baker, *supra* note 104, at 11.
[118] *Id*., at 36-7. *See also* Jonathan B. Baker, *The Case for Antitrust Enforcement*, 17(4) J. ECON. PERSP. 27, 43-45 (Autumn 2003) (estimating that "the benefits of antitrust enforcement as a whole are, at a minimum, 50 times the costs, creating a strong presumption in favor of robust enforcement).
[119] *See, e.g.,* Leslie, *supra* note 85.
[120] We refer to our discussion of information to be gleaned from personalized pricing, *supra* Part II.
[121] Gal, *Algorithms*, *supra* note 2, at 93.
[122] *See* John von Neumann, *First draft of a report on the EDVAC, in* 15 IEEE ANNALS HIST. COMPUTING 27, 33–34 (1993); Joseph E. Harrington Jr., *Developing Competition Law for Collusion by Autonomous Price-Setting Agents*, 14 J. OF COMPETITION LAW & ECONOMICS 331 (2018). Machine learning algorithms may be less predictable, as they change over time based on the feedback they obtain.
[123] Gal, *Algorithms, supra* note 2.

explainability of algorithmic decisions,[124] enforcers aided by computer and data scientists can gain more information about likely outcomes and suitable remedies.[125] Such algorithmic transparency may result from voluntary actions by market players, reverse-engineering, or mandatory disclosure. Note, however, that deciphering the decision-making processes of machine learning algorithms may be more difficult, as such algorithms continuously evolve and adapt their behavior based on a continuous stream of data.

Furthermore, enforcers can reduce informational costs by using computational antitrust – a nascent but rapidly growing field that uses AI tools to analyze market dynamics in antitrust enforcement – to overcome some current evidentiary and analytical limitations. AI tools can be used, for example, to detect patterns in market conduct that raise red flags,[126] to develop better predictive models, and to audit algorithms to determine the variables that might be most relevant for analysis, making data collection more focused and more efficient.[127] AI simulations can also assist regulators in predicting how market participants are likely to react to regulatory changes,[128] or in evaluating the potential evolutionary paths of AI-based algorithms used by market participants.[129] By potentially providing cheaper and better information, algorithms can also reduce error costs.

Of course, algorithms do not solve all information problems. Indeed, in a cat-and-mouse dynamic, market players might use algorithms to limit enforcers' ability to detect anti-competitive conduct. In one example, a study by Google Brain showed that algorithms can autonomously learn how and when to encrypt messages, given a specified secrecy policy, in order to exclude other algorithms from the communication.[130] Unless enforcers have a way of determining when the

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[124] An entire field of computer science is focused on increasing the explainability of algorithms. *See, e.g.,* Auste Simkute et al., *Explainability for Experts: A Design Framework for Making Algorithms Supporting Expert Decisions More Explainable*, 7 J. OF RESPONSIBLE TECH. (Oct. 2021).

[125] Algorithmic Competition – Note by Germany, DAF/COMP/WD(2023)61 at para. 40–57, https://one.oecd.org/document/DAF/COMP/WD(2023)61/en/pdf.

[126] *See, e.g.,* Stanford Computational Antitrust, *The Adoption of Computational Antitrust by Agencies: 2021 Report* (Thibault Schrepel & Teodora Groza ed., 2022); Anthony J. Casey &Anthony Niblett, *Micro-Directives and Computational Merger Review*, 1 STANFORD COMPUTATIONAL REVIEW 133, 133 (2021) (using AI to correct for both over- and under-inclusiveness in merger review).

[127] *Id*. Gal and Rubinfeld, *AI and Mergers, supra* note 10.

[128] For an overview of some computational tools *see, e.g*., Nicolas Petit and Thibault Schrepel, *Complexity-Minded Antitrust*, J. OF EVOLUTIONARY ECONOMICS (2023).

[129] Gal and Rubinfeld, *supra* note 10.

[130] *See generally* Martin Abadi & David G. Anderson, *Learning to Protect Communications with Adversarial Neural Cryptography* (2016) (unpublished manuscript), https://arxiv.org/pdf/1610.06918v1.pdf.

conduct of algorithms is hidden by such encryption, detection might be difficult.[131]

Furthermore, the use of algorithms might increase the data points necessary to reach a decision under existing rules. McSweeny and O'Dea provide an example affecting merger review.[132] They assume that an algorithm can distinguish those consumers who do not own a car, and are thus much more likely to buy a certain product online, from those who do own cars and will commonly also shop in brick-and-mortar stores. Six firms operate brick-and-mortar stores, three of which also operate online. Two firms that operate in both spheres wish to merge. An analysis focused only on the fact that the overall number of firms is reduced from six to five would enable the merger. Yet the merger also reduces the number of firms selling in the online segment from three to two, creating a highly concentrated market for consumers who live in households without a car.[133] Furthermore, each additional simultaneous dimension on which the algorithms can segment consumers to enable better price discrimination increases the number of relevant markets.[134] Thus, they argue, "a merger that might previously have required an analysis of competitive effects in one relevant product market may instead require antitrust enforcers to examine dozens, if not hundreds, of potential relevant product markets."[135]

Before suggesting a typology of effects and delving into concrete examples (Part IV), we draw from the discussion above and the framework offered by decision theory to establish several basic principles for the reexamination of competition laws in the age of algorithms.

First, extant rules should potentially be made more interventionist when algorithmic decision-making is more likely to result in anti-competitive effects than human decision-making, all else equal. This may imply the need for new prohibitions, moving from neutral presumptions – or even presumptions of legality – to presumptions of illegality, or reinforcing the strength of existing presumptions of illegality by raising the evidentiary bar for their effective rebuttal.

Second, when algorithmic decision-making is more likely to yield pro-competitive outcomes than human conduct, the changes in legal rules should go in the opposite direction. This may entail, for example, moving from a high burden of rebuttal for defendants to a high burden of rebuttal for plaintiffs.

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[131] Gal, *Algorithms*, *supra* note 2, at 89.

[132] Terrell McSweeny & Brian O'Dea, *The Implications of Algorithmic Pricing for Coordinated Effects Analysis and Price Discrimination Markets in Antitrust Enforcement*, 32(1) ANTITRUST 75, 77 (2017).

[133] *Id*., at 78.

[134] *Id*., at 79.

[135] *Id.*, at 79.

Third, where algorithms reduce enforcement costs by facilitating case-specific information collection and processing, their adoption by agencies, or by plaintiffs, should be accompanied by a preference for more rebuttable presumptions and fewer per se rules, all else equal.

Finally, and conversely, when the use of algorithms by market players increases enforcement costs, a shift towards per se rules may be warranted.

## IV. APPLICATION OF PROPOSED FRAMEWORK TO REAL-WORLD EXAMPLES: A TYPOLOGY

We now illustrate how the decision-theoretic framework sketched above can be applied to various competition law rules, both substantive and procedural, under the premise that market participants use algorithms. Changes in the profitability and competitive consequences of certain actions brought about by such use may require the redesign of optimal legal rules, insofar as such changes are sufficiently large to cause a re-assessment of (i) the relative plausibility attributed to pro- and anti-competitive effects of a given conduct, based on existing knowledge; (ii) the ratio of the two types of error costs; and/or (iii) the information costs required to collect and process case-specific evidence and estimate error costs in a given case.

We suggest a typology consisting of six distinct categories that capture the potential effects of algorithms on competition rules: stricter rules; no change in the legal rule; no change in the rule but stronger need for its application; laxer rules; new prohibitions; and new or changed indicators. These categories may differ in the number or importance of rules that fall under them, or the extent of the change needed in any existing rule. We leave these issues for future study.

Our goal here is not to provide an exhaustive analysis of the effects of algorithms on every rule driven by competition law. Rather, we aim to illustrate the kinds of analytical thinking and recalibration that are required in markets where algorithms have become a ubiquitous feature of the competitive environment, to ensure that the law keeps pace with the evolving technological landscape. Nonetheless, since algorithms are a general-use technology, the insights gained from the chosen examples, taken from different jurisdictions around the world, serve as indicators for the kinds of legal recalibration that may be warranted for additional rules. Accordingly, the proposed typology and the examples are designed to create a stronger foundation for a more holistic and adaptable approach to algorithmic decision-making in competition law.

### *1. Need for Stricter Rules*

In some settings, the use of algorithms creates a need for stricter rules. Existing rules (such as neutral presumption or a presumption of legality) should be replaced with stricter rules (such as a (rebuttable) presumption of illegality) when the use of algorithms (i) makes the anti-competitive narrative more persuasive and/or the pro-competitive narrative less persuasive, *ceteris paribus*, in light of the accumulated knowledge, and/or (ii) reduces the relative cost of false positive errors. In addition, changing a rebuttable presumption of illegality to an irrebuttable presumption is optimal when (i) and/or (ii) hold and the information costs necessary to collect and process the case-specific information required to rebut the presumption are increased.

This category is quite large, given that algorithms often challenge assumptions regarding the self-correcting power of markets. Accordingly, we provide four examples.

First, consider predation. As noted above, the use of algorithms increases the potential for predatory pricing, challenging Chicago school claims that predation is economically irrational.[136] Current U.S. law, affected by the Chicago view, adopts a high threshold for predatory pricing allegations.[137] Plaintiffs must prove not only that the monopolist is charging a predatory price, but that a reasonable prospect of recoupment of losses exists.[138] This test has proven difficult to meet.[139] This outcome is logical if one assumes that laxer rules will lead to more false positives, given that predatory pricing is nearly impossible.

Yet once we infuse decision theory with the effects of algorithms on the profitability and therefore the rationality of predation, application of the existing rules significantly increases the number and costs of false negatives. Furthermore, algorithms make predatory pricing harder to detect, increasing the need to sanction those instances that are detected.[140] Accordingly, a change in the legal presumptions and the resultant burdens of proof is required. We agree with several changes suggested by Leslie.[141] First, when determining whether prices were below the relevant measure of costs, enforcers should focus on the relevant transactions – those sales that took place at a price below cost, rather than on the defendant's aggregate profitability across sales, as

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[136] Section III *supra*.
[137] This section builds on Gal and Rubinfeld, *AI and Mergers, supra* note 10.
[138] *See, e.g.,* Herbert Hovenkamp, *The Areeda-Turner Test for Exclusionary Pricing: A Critical Journal*, 46(3) REV. OF INDUSTRIAL ORG. 209 (2015).
[139] Leslie, *supra* note 85. C. Scott Hemphill & Phil Weiser, *Beyond Brooke Group: Bringing Reality to the Law of Predatory Pricing*, 128 YALE L. J. 2048 (2018)(some cases have nonetheless survived dismissal or summary judgement).
[140] *Ibid*., at 101.
[141] *Id*.

some courts have done.[142] This is because algorithmic predation involves targeted below-cost pricing, allowing a firm to tempt its rivals' marginal consumers away while maintaining overall profitability.[143] Second, algorithms challenge the justification for the requirement that plaintiffs prove a dangerous probability of recoupment of losses.[144] This requirement is based, inter alia, on the assumption that absent recoupment, below-cost pricing does not harm consumers.[145] Yet targeted personalized pricing can harm the predator's inframarginal consumers. These consumers do not enjoy the below-cost price in the predation period, and also miss out on the cost reductions that could have resulted from earlier entry of a competitor into the market.

The second example involves the rules regulating tying and bundling, where the supply of one product is conditioned on the purchase of another product. Bundling, a form of tying, covers cases where two or more products are sold only if purchased together. In pure bundling, products are sold jointly in fixed proportions.[146] The economic literature identifies several main rationales for such conduct. One of the pro-competitive rationales involves a reduction in transaction costs. In their seminal paper, Salinger and Evans show that given high costs of determining which among the potential combinations is best for each consumer, it may be more efficient to create a limited number of bundles from which consumers can choose.[147] While such bundling reduces consumer choice, it increases output. This is because it reduces transaction costs for both the supplier and the consumer. Other rationales are anti-competitive. Most importantly, tying can serve as a foreclosure device to raise entry barriers for rivals.[148]

Accordingly, legal rules dealing with tying often require enforcers to engage in a rule-of-reason analysis to determine the relevance of the different rationales. The EU, for example, applies an effects-based approach to tying, which requires proof, inter alia, that there is no objective justification for the tying.[149] The U.S. also applies a rule of reason with a similar requirement.[150] Algorithms may move the needle, in

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[142] *Id*., at 102.
[143] *Id*., at 103.
[144] *Id*., at 108 (basing his argument on different reasons than those argued here).
[145] *Id*., at 108, citing to W. Parcel Express v. United Parcel Serv., 65 F. Supp. 2d 1052, 1063 (N.D. Cal.1998) ("Predatory pricing is only harmful when the predator succeeds in recouping the losses it suffered by its earlier below-cost pricing"), aff'd, 190 F.3d 974 (9th Cir. 1999).
[146] *See, e.g.,* Case T-210/01, *GE v. Commission* [2005] ECR II-5575, para 406.
[147] David S. Evans and Michael Salinger, *Why do Firm Bundle and Tie? Evidence from Competitive Markets and Implications for Tying Law*, 22 YALE J. ON REG. 37 (2005).
[148] Michael Winston, *Tying, Foreclosure and Exclusion*, 80 AMERICAN ECONOMIC REVIEW 837 (1990); Dennis Carlton and Michael Waldman, *The Strategic Use of Tying to Preserve and Create Market Power in Evolving Industries* 33 RAND J. OF ECONOMICS 194 (2002).
[149] Case T-201/04 *Microsoft* [2007] ER II-3601; Richard Wish and David Bailey, COMPETITION LAW 732-737 (8th ed., 2015). The burden of proof of the fifth requirement is on the defendant.
[150] *See, e.g., US v. Microsoft*, 235 F 3d 34 (DC Cir., 2001).

some situations, from a rule of reason to quick look. This is the case where a firm that raises the transaction-costs justification for offering a limited number of bundles with different features has relatively easy access to data on consumers' preferences. By reducing the costs of determining which bundle may best serve each consumer, data-based algorithms may enable more profitable (partial) unbundling. This is especially true where the production and distribution costs of different bundles are not prohibitive, such as with digital products and services. In such situations, a claim that bundling is required to reduce transaction costs may be weakened.

A third example focuses on the exchange of historic information among competitors. Information exchanges are analyzed under a rule of reason, given that they may have both pro- and anti-competitive effects, depending on the circumstances.[151] Exchange of historic data is generally allowed, since it is considered not to have a direct impact on the current or future competitive conduct of market participants.[152] Yet the analysis of such information by algorithms increases the probability that it can lead to coordination. This is because algorithms can more easily than humans detect patterns in such data, and use such information to determine how to maximize joint profits. This concern is heightened when historical data relates to decisions made by pricing algorithms, since its analysis may enable a firm to indirectly learn about the decision-making mechanisms of its rivals' algorithms, and predict their next moves. This enhanced ability weakens the ingrained assumption that exchanges of historical data are mostly harmless to competition, and increases instances of false negatives. It justifies adopting a stricter rule, at least with regard to certain types of historical data, such as a quick-look rule or shifting the burden of proof to the defendant.

The final, related example involves the exchange of information in hub-and-spoke scenarios, where rivals rely for their decisions on the same provider of algorithmic decision-making services.[153] Such algorithms can create both pro- and anti-competitive effects, depending, inter alia, on market conditions and on the specifics of the algorithm used (e.g., the origin of the input data, the parameters used by the algorithm, and how its outputs are employed by its users).[154] Some relevant questions focus on whether the parties shared data that is not as easily

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[151] *See, e.g.,* Guidelines on Horizontal Cooperation Agreements, OJ [2011] C 11/1.
[152] Case IV/36.069, Wirtschaftsvereinigung Stahl, OB L 1, 3.1.1998.
[153] EZRACHI & STUCKE, *supra* note 64. For their economic effects *see, e.g.,* Joseph E. Harrington Jr., *The Effect of Outsourcing Pricing Algorithms on Market Competition*, 68 MANAGEMENT SCIENCE 6889 (2022); LUKE GARROD, JOSEPH E. HARRINGTON JR. & MATTHEW OLCZAK, HUB-AND-SPOKE CARTELS: WHY THEY FORM, HOW THEY OPERATE, AND HOW TO PROSECUTE THEM (2023).
[154] *See also* Harrington, *ibid*.

obtainable otherwise, and whether the shared data enabled rivals to learn about the algorithms' decision parameters.[155]

Current U.S. case law is not sufficiently amenable to the task, creating false negatives. In *Gibson v. MGM Resorts* the plaintiffs alleged that hotels on the Las Vegas strip used third-party pricing software to aggregate their pricing information, and that this aggregation affected the pricing recommendations produced by the software, which were then used as a basis for pricing room offers.[156] The case was dismissed, without prejudice.[157] The court held, inter alia, that the plaintiffs failed to prove that the hotel operators were required to accept the prices recommended by the software.[158] A demand for proof of such a requirement is problematic, especially if each rival is aware of the fact that the algorithm receives similar data from all or most other market operators, and offers a similar profit-maximizing service to all. While such a requirement may not be optimal for human recommenders as well, algorithms strengthen the concerns raised by such a lenient rule. As firms become aware of the relative advantages of algorithmic price recommenders, the need for an explicit requirement that users accept its recommendations in order to sustain coordination is weakened. Indeed, as noted earlier in this article, a ProPublica investigation revealed a psychological effect of algorithmic recommenders, which strengthened the willingness of property managers to raise prices significantly and frequently.[159]

This ruling prompted some U.S. senators to recently introduce the Preventing Algorithmic Collusion Act, in order to close "loopholes in current law" that enable "automated price-setting algorithms [to] be

[155] Gal and Rubinfeld, *AI and Mergers, supra* note 10.

[156] Richard Gibson et al. v. MGM Resorts International et al., U.S. District Court, District of Nevada, No. 2:23-cv-00140. For cases in other jurisdictions *see, e.g.*, Press Release, Danish Competition and Consumer Auth., *Danish Competition Council: Ageras has infringed competition law* (June 30, 2020), https://www.en.kfst.dk/nyheder/kfst/english/decisions/20200630-danish-competition-council-ageras-has-infringed-competition-law/ (a digital platform for professional services created an illegal cartel when its algorithm suggested minimum prices that service providers should charge clients on the platform); Case C-74/14, *Eturas v. Competition Council of the Republic of Lithuania*, 4 C.M.L.R. 19 (2016) (the European Court of Justice found that a travel booking software program used by most Latvian travel agencies was employed as a tool for limiting price reductions on travel packages).

[157] Order, *Gibson*, No. 2:23-cv-00140-MMD-DJA (D. Nev. Oct. 24, 2023), ECF No. 141. The Department of Justice is investigating similar allegations against Texas-based RealPage, a provider of an algorithm that helps landlords set prices for apartments across the U.S. Heather Vogel, *Department of Justice Opens Investigation into Real Estate Tech Company Accused of Collusion with Landlords*, PROPUBLICA, Nov. 23, 2022, https://www.propublica.org/article/yieldstar-realpage-rent-doj-investigation-antitrust.

[158] Order, *ibid.*

[159] Heather Vogel, *Rent Going Up? One Company's Algorithm Could Be Why*, PROPUBLICA, Oct. 15, 2022, https://www.propublica.org/article/yieldstar-rent-increase-realpage-rent.

used to unfairly raise prices."[160] The Act creates, inter alia, a presumption of a price-fixing agreement when direct competitors share competitively sensitive information through a pricing algorithm in order to raise prices.[161] Such a presumption is well placed, as it overcomes the too lenient approach adopted by some courts, which puts insufficient weight on the increased abilities of algorithms and thereby increases false negatives.[162] Yet, as Harrington argues, this presumption might not have the desired outcome of avoiding the anticompetitive effect in all settings, given that coordination may arise even without such information sharing.[163]

### *2. No Change Required*

Some rules do not need to change simply because algorithms are involved. At a high level of abstraction, this is true of most rules. For example, a prohibition of conduct that abuses market power without offsetting justifications is appropriate regardless of whether algorithms are involved. Yet even from a less granular perspective, some rules are fit for both human and algorithmic decision-making. This is the case when the use of algorithms does not significantly change (i) the relative persuasiveness of the pro- and anti-competitive narratives, in light of the accumulated knowledge, (ii) the ratio of error costs, or (iii) the information costs necessary to rebut existing presumptions.

Consider, for example, proof of market power, which is a prerequisite in most competition law cases. Market power can be proven directly, based on evidence of supra-competitive trade conditions,[164] or indirectly, by analyzing the competitive pressures in the relevant market resulting from the ease of entry or expansion. In particular, should a firm enjoy a significant comparative advantage over its rivals, market power can be found to exist.[165]

The use of algorithms does not alter this econo-legal analysis. As elaborated above, algorithms can affect entry barriers and competitive pressures, depending on the circumstances. Consider a singular

[160] *Klobuchar, Colleagues Introduce Antitrust Legislation to Prevent Algorithmic Price Fixing - News Releases - U.S. Senator Amy Klobuchar* (senate.gov) (Feb. 2, 2024*). See also Preventing the Proposed Algorithmic Facilitation of Rental Housing Cartels Act of 2024*, https://www.congress.gov/bill/118th-congress/senate-bill/3692/text?s=1&r=109, which is specifically targeted toward rental housing pricing algorithms.
[161] *Ibid*.
[162] *See, e.g.,* Ariel Ezrachi & Maurice E. Stucke, *The Role of Secondary Algorithmic Tacit Collusion in Achieving Market Alignment* (2023), https://ssrn.com/abstract=4546889.
[163] Harrington, *Third Party, supra* note 47.
[164] This is a direct result of the Lerner Index. Abba P. Lerner, *The Concept of Monopoly and the Measurement of Monopoly Power*, 1(3) THE REVIEW OF ECONOMIC STUDIES 157 (1934).
[165] *See, e.g.,* Case AT.39740, Google Search (Shopping), Commission Decision of 27 June 2017, C(2017) 4444 final, https://ec.europa.eu/competition/antitrust/cases/dec_docs/39740/39740_14996_3.pdf, para. 286.

algorithm that significantly increases the efficiency of data analysis, enabling its user to save on restocking and shipment costs. Such an algorithm can create a significant comparative advantage for its user. Conceptually, such an algorithm is no different from any other tool that might create a comparative advantage, such as better production processes or intra-firm communication. All are merit-based superior capabilities that can potentially increase a firm's market power. The analytical framework applied to determine market power should thus be similar for all.

### *3. Same Rule, Stronger Need for its Application*

Algorithms may strengthen the need to apply an existing legal rule, without altering its content, thereby affecting enforcement priorities rather than legal substance. This need may arise when the use of algorithms does not justify altering the legal presumption (e.g., when an irrebuttable presumption of illegality already applies). Yet, ceteris paribus, algorithmic decision-making (i) increases the prevalence of an anti-competitive conduct that is already prohibited by law, and/or (ii) increases the costs of false negative errors should the prohibition not be applied, while not increasing the costs of false positive errors to the same degree, and/or (iii) reduces the information costs necessary to collect and process the case-specific information required to assess the relative anti-competitive and pro-competitive effects of said conduct (e.g., when the use of algorithms increases agencies' ability to track and understand the decisional mechanisms of market players).

To illustrate, consider the rule which enables enforcers to establish joint dominance (a shared monopoly) among a group of market players. Once proven, the prohibitions against abuse of dominance (monopolization) can then be applied to such a group.[166] This tool is rarely used. However, it can be aired to partially deal with algorithmic coordination.[167]

As elaborated above, under some market conditions pricing algorithms can lead to autonomous price coordination.[168] Despite the potent negative welfare effects of such conduct, fully autonomous price coordination by algorithms is not prohibited.[169] This is because the application of antitrust is conditioned on the existence of an "agreement" between firms to coordinate trade terms. Oligopolistic coordination – wherein each competitor sets his trade terms unilaterally while accounting for the plausible reactions of his rivals – is not considered an

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[166] See sources *infra*.

[167] Karsten T. Hansen, Misra Kanishka & Mallesh M. Pai, *Frontiers: Algorithmic Collusion: Supra-Competitive Prices via Independent Algorithms*, 40 MKTG. SCI. 1 (2021).

[168] Coutts, *supra* note 4.

[169] *Id.* at 33–42.

agreement.[170] Pure algorithmic coordination is a form of oligopolistic coordination, and is thus not prohibited.[171]

Declaring a group of competitors engaged in algorithmic coordination to be a joint monopoly opens an indirect route to tackle some of the negative welfare effects of algorithmic coordination. Application of this rule will subject the firms operating the algorithms to the legal restrictions imposed on monopolies. This is most useful in jurisdictions which prohibit exploitative conduct, since algorithmic coordination does not generally involve exclusionary conduct.[172]

Such a declaration can be based on existing laws. Take, for example, EU case law, which defines joint dominance as "two or more independent economic entities…united by such economic links that together they hold a dominant position vis-à-vis the other operators on the same market,"[173] "provided that from an economic point of view they present themselves or act together on a particular market as a collective entity." [174] In *Compagnie Maritime Belge*, the European Court of Justice clarified that proof of joint monopolization did not require any explicit agreement or structural link such as shareholding.[175] Rather, such a link could also be a mere expression of the economic structure of the market – such as an oligopoly.[176] This opened the door to effectively capturing situations of tacit coordination that escaped the prohibition against agreements in restraint of trade.[177] Concerns regarding the penalizing of rational economic conduct[178] led the EU General Court to set three criteria that must be examined in an integral manner

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[170] Theatre Enter. Inc. v. Paramount Film Distrib. Corp., 346 U.S. 537, 541 (1954) ("[T]his Court has never held that proof of parallel business behavior conclusively establishes agreement or, phrased differently, that such behavior itself constitutes a Sherman Act offense"). *See also* E.I. Dupont de Nemours & Co. v. FTC, 729 F.2d 128, 139 (2d Cir. 1984) ("The mere existence of an oligopolistic market structure in which a small group of manufacturers engage in consciously parallel pricing of an identical product does not violate the antitrust laws").
[171] Gal, *Algorithms*, *supra* note 2.
[172] OECD, *Excessive Pricing,* DAF/COMP(2011)18 (2011), https://www.oecd.org/competition/abuse/49604207.pdf. In some jurisdictions prohibitions may also directly relate to conduct that make it easier to engage in the abusive conduct, such as making the algorithms or the datasets transparent to rivals.
[173] Joined cases T-68/89, T-77/89 and T-78/89, Società Italiana Vetro SpA, Fabbrica Pisana SpA and PPG Vernante Pennitalia SpA v Commission [1992] ECR II-1403.
[174] Joined Cases C-395/96 P and C-396/96 P Compagnie Maritime Belge Transports and Others v Commission [2000] ECR I-1365.
[175] *Id*. *See also* Alexandre Verheyden & Jorge Padilla, *Joint Dominance in The New European Electronic Communications Code: An Opportunity To Ensure Consistency & Legal Certainty* Jones Day (September 2017), https://www.jonesday.com/en/insights/2017/09/joint-dominance-in-the-new-european-electronic-communications-code--an-opportunity-to-ensure-consistency--legal-certainty.
[176] Compagnie Maritime Belge, *ibid*.
[177] Verheyden & Padilla, *supra* note 175, at 12.
[178] *Ibid*.

(the "*Airtours* test").[179] First is the *transparency* requirement: each member of the oligopoly must be able to monitor the conduct of other members, so as to determine whether they are adopting the common policy. The second requirement is *sustainability of tacit coordination*: tacit coordination must be sustainable over time, meaning that there must be an incentive for the members not to depart from the common policy in the form of a deterrence/monitoring mechanism and adequate retaliation in case of deviation. And third is a *lack of competitive constraints*: the foreseeable reaction of current and future competitors or consumers must not jeopardize the results of the common policy. Yet while the test was lauded for its economic soundness, in practice, the Commission did not apply the concept of joint dominance in any additional case involving an abuse of dominance.[180]

As elaborated by Gal elsewhere, algorithms can make it easier to apply the three-pronged *Airtours* test.[181] The *transparency* requirement can be met by employing monitoring algorithms. Such algorithms can often collect and analyze the necessary data on market conditions more quickly and efficiently than humans.[182] Also, the fact that the algorithm is a "recipe for action" makes it easier both to monitor its decisions, either directly (when the algorithm itself is transparent to rivals) or indirectly (by reverse-engineering the algorithm given a sufficiently large number of data points on its previous actions), and to correctly predict how the algorithm will react to a given set of data.[183] Indeed, communication to competitors of future intended actions can often be performed by simply making one's algorithm transparent and readable by (select) others' communication protocols.[184] The *sustainability of tacit coordination* requirement is also more easily met by algorithms.[185] Algorithms can more efficiently, cheaply, and swiftly monitor, analyze, and act upon deviations from the status quo. Also, their high levels of sophistication make it easier to differentiate between intentional deviations from the status quo and natural reactions to changes in market conditions or even errors, thereby preventing unnecessary price wars.[186] Furthermore, in retail ecommerce settings the incentives to deviate in the first place are reduced. Since the algorithm can react almost immediately to changes in a competitor's price, and transactions are

[179] Airtours, *supra* note 71. While this test was established in the context of merger regulation, it was later made clear that it also applied to ex post assessments. Cases T-191/98 and T-212/98 joined to T-214/98, Atlantic Container Line AB and Others v Commission [2003] ECR II-3275.
[180] Airtours, *ibid*.
[181] Gal, *Algorithms, supra* note 2. The Airtours test resembles Stigler's conditions for coordination. Stigler, *supra* note 40.
[182] Gal, *ibid*., at 78-9
[183] Salcedo, *supra* note 53.
[184] Gal, *Algorithms, supra* note 2.
[185] *Ibid*.
[186] *Id*, at 88.

small and frequent, the ephemeral price will not significantly increase the deviating firm's profit in the short term, while potentially reducing its profits in the longer term if other firms immediately follow. Accordingly, the benefits from deviation are likely to be small and temporary.[187] The third condition, *lack of competitive constraints*, is not affected by the use of algorithms, unless algorithms enable firms to engage in exclusionary conduct.[188] Yet the mere fact that the use of algorithms can lead to sustained parallel pricing may serve as indirect proof of this condition. Accordingly, it might be time to apply joint dominance where the regulator can impose a remedy to reduce anti-competitive harms.[189]

Another example of a tool that need not be changed, but that can be applied more frequently to help limit instances of algorithmic coordination, is the prohibition of facilitating practices.[190] Facilitating practices are positive, avoidable actions that help competitors overcome impediments to coordination, in a way that goes beyond mere interdependence.[191] The use of facilitating practices can serve as an indirect, circumstantial indication of agreement between parties operating in the market.[192] Certain types of conduct involving algorithms can be used as facilitating practices, such as making one's algorithm and dataset transparent to rivals, where such transparency does not benefit consumers.[193] While not a panacea, this existing legal tool can reduce the occurrence of coordination in some instances.

#### *4. Need for Laxer Rules*

Algorithms may justify a potential relaxation of certain competition law rules. For example, it would be appropriate to substitute an irrebuttable presumption of illegality for a rebuttable presumption of illegality if the information costs involved – i.e., the costs of collecting and processing the case-specific information required to rebut the presumption – fall to the point where they are lower than the error costs resulting from use of the additional information, even if those error costs also fall. Furthermore, the presumption of illegality should be replaced by a presumption of legality if the use of algorithms (i) makes

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[187] *Id*.
[188] For a review of such studies see Gal and Rubinfeld, *AI and Mergers, supra* note 10.
[189] For difficulties in shaping such a remedy see, e.g., Gal, *Algorithms, supra* note 2.
[190] *Ibid*.
[191] *See, e.g.*, Steven C. Salop, *Practices that (Credibly) Facilitate Oligopoly Coordination*, *in* NEW DEVELOPMENTS IN THE ANALYSIS OF MARKET STRUCTURE 265, 271 (Joseph Stiglitz & G. Frank Mathewson eds., 1985); Charles A. Holt & David T. Scheffman, *Facilitating Practices: The Effects of Advance Notice and Best-Price Policies*, 18 RAND J. ECON. 187 (1987).
[192] *See, e.g.*, William H. Page, *Facilitating Practices and Concerted Action under Section 1 of the Sherman Act*, *in* ANTITRUST LAW AND ECONOMICS 23 (Hylton ed., 2010).
[193] Gal, *Algorithms, supra* note 2, at 98, 110.

the anti-competitive narrative relatively less persuasive, and/or the neutral or pro-competitive narrative relatively more persuasive, *ceteris paribus*, in light of the accumulated knowledge, and (ii) increases the costs of false positive errors, and/or reduces the costs of false negative errors, relative to the other type of costs.

Consider the legal requirement that consumer welfare be analyzed independently in each relevant market, implying that gains in one market cannot be balanced against losses in another. Accordingly, if a targeted group of consumers that constitute a separate, relevant market are harmed, and such harm cannot be efficiently remedied, this in and of itself is sufficient grounds to justify blocking the transaction.[194] Such a rule is prevalent in many jurisdictions, especially in merger review.[195]

Now enter algorithms. As elaborated above,[196] the increased ability of algorithms to determine each consumer's WTP can lead to narrower (sub)markets, some potentially consisting of just one consumer. As McSweeney and O'Dea argue, this leads to two main problems.[197] First, to ensure that no consumer is harmed, a transaction that might previously have required an analysis of competitive effects in one relevant product market may instead require regulators to examine dozens, if not hundreds, of potential relevant product markets – a resource-consuming endeavor, implying that information costs will increase.[198] Second, the fracturing of relevant product markets on the basis of price discrimination could increase the chances that a given transaction will harm consumers in some relevant market. To illustrate, consider a horizontal merger that has the potential to create synergies that will significantly lower the merged firm's production costs. Yet the merger will also increase the ability of the merged firm's algorithms to engage in personalized pricing. While marginal consumers stand to significantly benefit from the merger, a small group of inframarginal consumers will be harmed by it. While such scenarios arise even without algorithms, greater use of algorithms increases their prevalence. First, algorithms increase the ability to single out inframarginal consumers and engage in price discrimination. Second, fashioning appropriate structural remedies to limit algorithmic price discrimination is a challenging task, especially since price discrimination markets are defined on the basis of consumers' WTP.[199]

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[194] *Id*.
[195] *See, e.g.,* Case C-501/06 P, GlaxoSmithKline Services Unlimited v Commission of the European Communities, Judgment of the Court (Third Chamber) of 6 October 2009, ECLI:EU:C:2009:610; Case C-382/12 P, MasterCard Inc. and Others v European Commission, Judgment of the Court (Third Chamber) of 11 September 2014, ECLI:EU:C:2014:2201.
[196] Section III.3 *supra.*
[197] McSweeny & O'Dea, *supra* note 132.
[198] *Ibid*.
[199] *Id*., at 79.

Under the existing rule, there is a stronger chance that the transaction will be blocked even if significant synergies are created and overall consumer welfare is significantly increased.[200] This concern is particularly acute in jurisdictions where regulators, like the U.K.'s Competition and Markets Authority, require structural remedies to counter the anti-competitive effects of a horizontal merger.[201] Such rules are based on the assumption that the costs of prohibiting mergers in which a structural solution is not possible (false positives) are lower than the costs of enabling them (false negatives) and/or enforcing alternative behavioral solutions. In the age of algorithms, a strict structural-solution-only rule will prevent more mergers that could potentially increase consumer welfare, if inframarginal consumers (might) constitute a separate market.

McSweeney and O'Dea suggest two partial solutions.[202] The first is to apply behavioral remedies, which are better suited to ensure that synergies can be realized without harm to consumers. Optimally, two sets of complementary remedies should be applied: structural remedies to protect marginal consumers, and behavioral remedies to protect inframarginal ones. For instance, prices for the latter might be tethered to prices for the former, limiting price discrepancies and enabling otherwise procompetitive mergers to be approved.[203] The second is more fundamental, and suggests adopting a laxer rule, by which enforcers would be allowed to exercise prosecutorial discretion to permit a transaction where the overall benefit to consumers clearly and materially outweighs harm to targeted consumers that cannot be remedied without blocking the transaction.[204] We further suggest exploring whether the application of a laxer rule should be dependent on the ability to engage in a quick-look analysis, in order to reduce information costs.

A second example involves a procedural rule designed to deal with the increased information costs of potential plaintiffs which result from the use of a pricing algorithm. As Leslie argues, while in the past plaintiffs could generally easily discern the relevant price, assessing prices is much more difficult in the era of pricing algorithms.[205] This is because such algorithms can strengthen firms' ability to engage in personalized pricing, where a single product can have numerous different

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[200] *Id*.
[201] This is reflected, *inter alia*, in the British Competition and Markets Authority, Anticipated Acquisition by Microsoft Corporation of Activision Blizzard, Inc., first phase decision (September 1, 2022) https://assets.publishing.service.gov.uk/media/634536048fa8f5153767e533/MSFT.ABK_phase_1_decision_-_1.09.2022.pdf.
[202] *Id*.
[203] *Ibid*.
[204] *Id*.
[205] Leslie, *supra* note 85, at 105.

prices that vary by consumer, and might change over time.[206] This shift toward more personalized pricing, in turn, may increase the need for more lenient rules towards pre-trial discovery of prices. Applying a more lenient approach towards such pre-trial discovery where the plaintiff can show a prima-facie basis for anti-competitive conduct can potentially decrease the plaintiff's information costs and reduce false negative errors. Absent such discovery, it will be more difficult to prove illegal predation, supra-competitive selective pricing, or discrimination, all of which have become easier and more profitable in the age of algorithmic decision-making. Of course, the increased costs such discovery imposes on the defendant should also be taken into account when designing the optimal discovery rule. Yet algorithms can also help reduce such costs by collecting, organizing, and saving pricing information automatically.

### 5. *Need for New Prohibitions*

Algorithms may also create a need for new prohibitions. Such a need may arise where any of the following hold: (i) a certain type of anticompetitive conduct was not known or not given sufficient weight when designing existing rules, leading, *ceteris paribus*, to a significant increase in false negatives in light of the law's goals; (ii) the current law's focus on a certain "legal hook" for liability no longer fits the type of conduct algorithms can engage in; or (iii) information costs are reduced to such a degree that it is now cost-effective to separate pro- from anti-competitive cases.

Consider pure autonomous algorithmic coordination, which exemplifies both the first and the second scenarios. Such coordination does not create a new *type* of harm, as it is typically a form of oligopolistic coordination.[207] As elaborated above, current regulation of oligopolistic coordination is limited,[208] partly because it was not perceived as a pervasive market issue, given the stringent conditions required for its occurrence.[209] Yet algorithms can increase the *extent* of harm, given that their ability to overcome certain barriers to coordination diminishes the disciplining force of competition.[210] This warrants a re-examination of approaches to address such conduct.

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[206] *Ibid*. Cheng emphasizes that personalized pricing is distinct from first-degree price discrimination, in that it does not require the seller to exhaust every consumer's willingness to pay. Rather, the seller charges every customer a tailored price based on his personal characteristics. Thomas K. Cheng, *Tying in the Age pf Algorithms,* THEORETICAL INQUIRIES IN LAW (2024).

[207] See discussion in this sub-section *infra*.

[208] See discussion in section II.3.a *supra.*

[209] In the US context, *see* David Scheffman, *Commentary on "Oligopoly Power, Coordination and Conscious Parallelism," in* NEW DEVELOPMENTS 295.

[210] See discussion in section II.3.a *supra*.

Scholars have proposed various reforms to capture such algorithmic coordination.[211] Here we review two. Kaplow proposes to treat conscious parallelism as an "agreement," adopting Posner's view that oligopolistic coordination can linguistically and even conceptually be defined as such, as it has elements of offer and acceptance.[212] However, this proposal fails to address the more complex issue of precisely defining the objectionable conduct and crafting an appropriate remedy that would not require persistent judicial oversight.[213] Furthermore, as Van den Boer, Meylahn, and Schinkel have recently argued, some types of algorithmic supra-competitive parallel pricing may not amount to coordination in the economic sense, making it more difficult to prove offer and acceptance.[214] Coordination is defined in economics as a process of reward and punishment.[215] This reward–punishment dynamic is regarded as an essential condition for coordination to arise. Yet recent studies have demonstrated that algorithms can learn to raise prices in parallel even in the absence of a such a dynamic.[216] Such studies deployed memoryless algorithms or algorithms with no punishment mechanism, which nonetheless converged on supra-competitive parallel pricing under some market conditions.[217] This phenomenon also compounds enforcement challenges: even if oligopolistic coordination is deemed an "agreement," regulators may struggle, based solely on observed prices, to distinguish it from parallel pricing that did not arise from a reward–punishment dynamic.

Other scholars have suggested changing the law to be process-based (i.e., regulating the process or mechanism that leads to coordination), rather than focusing on the existence of an agreement or communication between the parties.[218] For example, Calvano, Calzolari, Denicolò, Harrington, and Pastorello suggest shifting the regulatory focus from communication to the coordinating pricing rules learned by the algorithm.[219] This implies prohibiting use of those parts of the algorithm's code which produce a predictable coordinated outcome, while ensuring that the efficiency gains from using such algorithms are

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[211] For elaboration, see Gal, *Algorithms*, *supra* note 2.

[212] RICHARD A. POSNER, ANTITRUST LAW: AN ECONOMIC PERSPECTIVE 146 (1976); Richard A. Posner, *Oligopoly and the Antitrust Laws: A Suggested Approach*, 21 STANFORD L. REV. 1562, 1562 (1969). Posner later changed his mind. *See* Richard Posner, *Review of Kaplow, Competition Policy and Price Fixing*, 79 ANTITRUST L.J. 761 (2014).*See also* LOUIS KAPLOW, COMPETITION POLICY AND PRICE FIXING (2013).

[213] *See, e.g.,* Gal, *Limiting, supra* note 4.

[214] Den Boer *et al., supra* note 67.

[215] Stigler, *supra* note 40.

[216] Den Boer et al., *supra* note 67.

[217] For such studies *see, e.g.,* Ibrahim Abada & Xavier Lambin, *Artificial Intelligence: Can Seemingly Collusive Outcomes Be Avoided?*, 69(9) MANAGEMENT SCIENCE (2023); Asker *et al., supra* note 6.

[218] Focus on economic effects, rather than on communication, was also suggested in the non-algorithmic context. Posner, *supra* note 212; Kaplow, *supra* note 212.

[219] Calvano et al., *Protecting Consumers, supra* note **Erreur ! Signet non défini.** 52.

not lost.[220] This solution builds on the differences between humans and algorithms, mainly the fact that algorithms can be audited to determine what led to coordination (correlations, even if causality is not explained), thereby limiting the need to focus on communication.[221] It also goes to the root of the problem – to the conduct which facilitates coordination.[222] Yet, as Gal elaborates elsewhere, significant problems arise in its application. These include identifying the pricing rules that lead to coordination and distinguishing them from other parts of the code, especially where a learning algorithm is involved.[223] But the biggest challenge is ensuring that prohibiting use of the code necessarily leads to increased welfare, and that the efficiency gains from using such algorithms are not lost. This is especially true where proscribing only the problematic bit of code may be impossible, implying that the use of certain learning algorithms might be prohibited altogether.[224] This challenge is further exacerbated by the ability of algorithms to reach supra-competitive pricing in some situations simply by reacting to market conditions in each period anew.[225] Accordingly, the challenge of effectively regulating algorithmic coordination persists, necessitating novel thinking.

### 6. *Need for Alternative Indicators*

Algorithms also create a need for alternative legal indicators of anti-competitive harm, indicators better tailored to the market dynamics that algorithms engender and the associated informational costs. The need for new indicators arises, inter alia, where algorithms (i) significantly increase the error or information costs involved in applying existing indicators, and/or (ii) reduce the error or information costs of using alternative indicators. We offer three examples.

The first example arises from the recent U.S. merger guidelines,[226] which contain several indicators for substantial competition. One such indicator focuses on "the monitor[ing of] each other's pricing, marketing campaigns, facility locations, improvements, products, capacity, output, and/or innovation plans. This can provide evidence of competition between the merging firms, especially when they react by taking steps to preserve or enhance the…profitability of their own products or services."[227] As Gal and Rubinfeld argue, seen through the lens of algorithmic coordination, monitoring and taking steps to preserve one's

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[220] *Ibid*., at 1041.
[221] *Id*.
[222] Gal, *Algorithms, supra* note 2.
[223] *Ibid*.
[224] *Id*.
[225] See discussion in the previous paragraph.
[226] Based largely on Gal and Rubinfeld, *AI and Mergers, supra* note 10.
[227] DEP'T JUST. & FED. TRADE COMM'N, MERGER GUIDELINES ¶2 (2023).

profitability can lead to coordination rather than competition. Indeed, conduct that signals competition in (most) traditional markets might lead to parallel coordination when algorithms are used.

The second example involves the extent of asymmetries and heterogeneities among market participants, which inform assessments of the expected degree of competitive harm.[228] Reliance on such indicators is predicated on the assumption that asymmetries and heterogeneities safeguard competition by impeding firms' ability to coordinate. Enter algorithms. While it is still true that firms are better able to estimate the cost structure, production capacity, and other key supply conditions of homogenous competitors compared to heterogenous ones, algorithmic predictive modeling can help firms better estimate the conditions and motivations of their heterogenous competitors.[229]

A third example relates to structural presumptions used to screen mergers.[230] Current laws are predicated on the assumption that oligopolistic coordination can take place only in highly concentrated markets. Accordingly, concentration parameters are given substantial weight in determining intervention thresholds.[231]

For instance, U.K. merger guidelines embody the assumption that mergers in markets with more than three players are not prone to coordination.[232] Algorithmic coordination challenges that assumption, given that algorithms can increase the number of firms that can potentially coordinate effectively. Accordingly, high levels of concentration should be given less weight in markets prone to algorithmic coordination.[233] The appropriate threshold levels, and the market conditions under which they should apply, warrant careful economic analysis.[234] The OECD suggested lowering the threshold to capture five-to-four transactions.[235] Ezrachi and Stucke suggested lowering it still further, to transactions involving five or even six significant players.[236] Yet even such thresholds might not be sensitive to the challenges posed by algorithmic pricing, where under some market conditions, algorithms may enable coordination even beyond those thresholds. Take, for example, the use of follow-thy-leader pricing algorithms in markets where

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[228] Gal and Rubinfeld, *AI and Mergers, supra* note 10, at 706-7.
[229] *See, e.g.,* Coutts, *supra* note 4, at 15-22.
[230] See Gal, *Algorithms, supra* note 2, at 216.
[231] *See, e.g.,* U.K. Competition & Mkts. Auth, Merger Assessment Guidelines ¶ 1.5 (2010).
[232] *Ibid*.
[233] Coutts, *supra* note 4.
[234] Gal, *Algorithms*, *supra* note 2, at 215.
[235] Org. For Econ. Co-Operation & Dev. (OECD), *Algorithms and Collusion: Competition Policy in the Digital Age* 41 (Sept. 14, 2017), https://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm.
[236] Ariel Ezrachi & Maurice E. Stucke, *Two Artificial Neural Networks Meet in an Online Hub and Change the Future (Of Competition, Market Dynamics and Society)* (Univ. Tenn. Coll. L., Legal Stud. Rsch. Paper Ser. No. 323, 2017), at 31.

products and firms are highly homogenous, transactions are frequent, and price matching is instantaneous. Under these conditions, assuming all firms but the leader use the algorithms, the benefits from lowering prices are miniscule.[237] Furthermore, as Coutts suggests, determining intervention levels should relate not just to the number of market players, but to other market conditions that affect algorithmic coordination, such as transparency and frequency of interactions.[238] This implies that intervention thresholds might have to be more sensitive to industry-specific conditions.

## VI. CONCLUSION

Algorithms are quickly becoming essential tools for decision-making in the marketplace. Their speed and sophistication can increase competition and efficiency. At the same time, the use of algorithms can potentially increase the ability of market players to engage in and profit from anti-competitive practices. In some cases, algorithms raise entry barriers for certain competitors, limiting their ability to participate effectively in the market. Paradoxically, while algorithms can reduce market frictions, this may not always lead to improved competition, as traditionally assumed. As a result, the changing market dynamics brought about by these technologies necessitate a reevaluation of the economic assumptions underpinning current competition laws to ensure they remain effective in promoting fair competition.

In recent years, researchers have made significant contributions to our understanding of how algorithms influence market dynamics.[239] While existing studies typically focus on specific contexts, this article develops a meta-framework for systematically analyzing the effects of algorithms on optimal competition laws. By identifying several categories of algorithmic effects and then applying decision theory, we created a typology consisting of six distinct ways in which algorithms impact existing competition laws. These effects range from necessitating stronger application of an existing law to requiring more lenient rules or entirely new legislation. Many of these effects arise from the challenging of economic presumptions embedded in competition laws. Each effect was illustrated with relevant examples drawn from current competition rules.

We show that while existing laws serve as a basis for tackling anticompetitive behavior, the distinctive features of algorithm-driven markets call for the creation of new prohibitions or the modification of current legal frameworks. It is thus time to review, revise, and refine

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[237] Gal, *Algorithms*, *supra* note 2, at 85–86.
[238] Coutts, *supra* note 4.
[239] *See, e.g.*, papers cited throughout this article.

current antitrust presumptions in line with the significant increase in the use of algorithms by market participants.

By highlighting these emerging challenges, we hope to stimulate further discussion and research into potential regulatory responses that can ensure a fair and competitive digital landscape.

The decision theory framework also emphasizes the need to reconsider not only the rules, but also the composition of regulatory decision-making bodies. In particular, decision-makers must include individuals with the expertise required to determine the extent of error costs based on given information. Competition authorities should therefore employ teams that include computer and data scientists when analyzing cases.

We leave for future research the interactive dynamics that emerge once the use of algorithms by consumers[240] and by regulators[241] is added to the analysis. We also leave for future analysis a deeper examination of cases where only some firms in a specific market use algorithms.[242]

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[240] Michal S. Gal & Niva Elkin-Koren, *Algorithmic Consumers*, 30 HARV. J.L. & TECH. 309 (2017).

[241] The growing field of Computational Antitrust is aimed at creating such tools. *See, e.g.*, STANFORD COMPUTATIONAL ANTITRUST, THE ADOPTION OF COMPUTATIONAL ANTITRUST BY AGENCIES: 2021 REPORT (Thibault Schrepel & Teodora Groza ed., 2022).

[242] Harrington shows that firms' adoption decisions can be strategic complements; that is, it is more profitable to adopt a pricing algorithm when other firms do so. Harrington, *Outsourcing, supra* note 153.