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## Collusion by Pricing Algorithms in Competition Law and Economics

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## Abstract

Software programs based on algorithms have become common in pricing because they outperform humans at automatising tasks in terms of speed, complexity, and accuracy of analysis. In many online markets, repricing algorithms have replaced the human decision-maker. As with any other technology employed in the market, repricing algorithms empower human activity toward both positive and negative consequences. Their properties enable market transparency and efficiencies but also entail collusion risks beyond traditional oligopolies. This paper analyses why repricing algorithms can facilitate anti-competitive coordination and what is the scope for Art. 101(1) TFEU to tackle it. Acknowledging the limitations of EU competition law against collusion by autonomous algorithms, we qualify the antitrust concern through the economics and computer science understanding of pricing algorithms. Algorithmic pricing does not always lead to higher prices, although even simple algorithms can learn complex reward-punishment schemes that resemble collusive pricing strategies.

## Keywords

antitrust, artificial intelligence, anti-competitive agreements, concerted practices

# 1. Introduction

In the exciting and challenging time when computer and data sciences enter the legal realm, the technical and legal questions raised by algorithmic decision-making have reached competition policy. Artificial intelligence ('AI') is a general-purpose technology and its applications have started to permeate many economic sectors.[1] Decreasing costs of data storage has enabled the accumulation of vast amounts of data ('Big Data') and more accessible high-performance computing, combined with high-speed connectivity for cloud applications, have enabled companies to exploit their data in novel ways.[2]

Competition agencies have identified algorithms as an enabler that allows firms to adapt their strategies, including more complex pricing and monitoring while changing the way competition takes place.[3] Pricing, content moderation, translation and online advertisement are among the many activities relying on specialised algorithms.[4] As the number of firms adopting algorithms increases, so does the pressure on rivals to follow suit, meet the competition and innovate through them, enlarging their use ever more.[5]

Algorithms are so ubiquitous because they can outperform humans at automatising tasks in terms of speed, complexity, and accuracy of analysis.[6] As with any other technology employed in the market, they empower human activity toward both positive and negative consequences. Efficiencies and quality improvements in products and services are among their expected benefits for both firms and consumers. However, many things can go wrong with automated decision processes. Undesirable outcomes range from censorship, privacy breaches, discrimination, democracy impairment, market power abuses and, for what is of interest here, collusion.[7]

Since the seminal book of Ezrachi and Stucke,[8] competition policy has acknowledged algorithmic collusion, that is, the coordination between firms' pricing algorithms leading to higher prices and reduced competition in the market. Antitrust lawyers have explored both how the law, as it is, could catch forms of ordinary price-fixing cartels implemented through algorithms and its limits vis-à-vis tacit collusion by autonomous algorithms. After the legal wave, a rapidly growing economics and computer science literature has approached algorithmic pricing from different angles, making predictions about the behaviour of algorithms based on simulations or economic theory and studying their effects on prices empirically. The lawyers' initial concerns that pricing algorithms would always find collusive strategies with each other have been severely qualified. Instead, researchers have found evidence of higher prices because of algorithmic pricing only in specific cases and conditional on market structure.

1 Nicholas Crafts, 'Artificial intelligence as a general-purpose technology: an historical perspective' (2021) 37 Oxford Review of Economic Policy 521. A survey by McKinsey finds that most respondents across different industries have adopted AI in at least one business function, see McKinsey & Company, 'The state of AI in 2023: Generative AI's breakout year' (2023)

2 Avigdor Gal, 'It's a Feature, not a Bug: On Learning Algorithms and what they teach us' (OECD DAF/COMP/WD(2017)50, 2017), 3. For an early analysis of the characteristics of Big Data, see Doug Laney, *3D Data Management: Controlling Data Volume, Velocity and Variety* (2001).

3 Autoridade de Concorrência, *Digital Ecosystems, Big Data and Algorithms* (Issues Paper, 2019), 41.

4 OECD, *Algorithmic Competition* (2023, OECD Background note DAF/COMP(2023)3), 8-9; Autorité de la Concurrence and Bundeskartellamt, *Algorithms and Competition* (2019), 4ff.

5 OECD, Algorithms and Collusion: Competition Policy in the Digital Age (2017), 22.

6 Michal Gal, 'Algorithms as Illegal Agreements' (2019) 34 Berkeley Technology Law Journal 68, 79.

7 OECD (2017), 44. For example, management scholars have provided alternative perspectives on pricing algorithms: Gerlick and Liozu suggest that ethical considerations including fairness, (avoiding) deception, and social justice, as well as legal considerations regarding data privacy and non-discrimination are more important than antitrust concerns to firms that deploy pricing algorithms; see Joshua Gerlick, Stephan Liozu, 'A Conceptual Framework of Ethical Considerations and Legal Constraints in the Algorithm-Driven Pricing Function' (2019) SSRN-id3454123.

8 Ariel Ezrachi and Maurice Stucke, Virtual Competition: The Promise and Perils of the Algorithm-Driven Economy (Harvard University Press, 2016).

Nonetheless, the EU regulatory push for digital markets' transparency has been suggested to increase future risks of algorithmic collusion.[9] Indeed, collusion by pricing algorithms might be the side effect of the many new obligations on data portability, data sharing, and artificial intelligence transparency that pursue fairness and contestability goals but neglect the anti-competitive risks of transparent markets populated by algorithms.[10] Arguably, the EU data policy pays lip service to Art. 101(1) TFEU, especially to the current Horizontal Cooperation Guidelines.[11]

Taking stock of the recent, more technical research on the effect of pricing algorithms on market outcomes, this paper analyses pricing algorithms under Art. 101(1) TFEU. It provides an understanding of the key technical, economic, and legal notions behind algorithmic collusion as they developed in the literature and, so far, limited case law. Section 2 introduces the information technology concepts of AI-based algorithms, their pricing applications, and possible competitive facets. Section 3 zooms in on algorithmic collusion: it distinguishes collusion from the EU law and economic perspectives before analysing why pricing algorithms can facilitate coordination and what are the predicted theories of harm. Section 4 traces how our understanding of pricing algorithms evolved in parallel through theoretical and empirical studies. We show how our understanding of the behaviour of pricing algorithms moved from catastrophic predictions to a carefully qualified assessment of the risk of collusion by autonomous algorithms with studies on market outcomes.

## 2. From Algorithms to Dynamic Pricing Algorithms

### *A. Algorithms, Machine Learning and Deep Learning*

Algorithms are finite sequences of instructions to solve calculations or problems in definite automated ways.[12] They may rely on simple rules or highly complex commands, yet they always automate computational procedures to generate outputs based on given information inputs.[13] Decision trees, plain language, software code and a combination of language and software code (so-called pseudo-code) are among the common ways to represent algorithms.[14]. The writer of an algorithm determines what kinds of information are incorporated into algorithm design, what sort of data to gather or ignore, how to use such data and how to pursue given objectives with it, including any limitations. Such ex-ante instructions and the context of operation determine how algorithms behave.[15]

Static algorithms with a finite number of responses to specific contingencies have long existed. 'Static' means that the algorithm only changes with the coders' intervention.[16] More recently, applications of AI involve self-learning algorithms that can adapt to changes in their environment. Generally, self-learning algorithms iteratively learn from the data they encounter and experience how to perform tasks in unknown and evolving settings with little or no human instruction. Accordingly, self-learning algorithms are particularly useful in changing environments, such as real markets, and

9 Michal Gal, 'Limiting Algorithmic Coordination' (2023) 38 Berkeley Technology Law Journal 173, 196.

10 See, for instance, Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC, OJ (2016) L119/1, Art. 20; Regulation (EU) 2022/868 of the European Parliament and of the Council of 30 May 2022 on European data governance and amending Regulation (EU) 2018/1724, OJ (2022) L 152/1, Arts. 4-5 and 10; Regulation (EU) 2022/1925 of the European Parliament and of the Council of 14 September 2022 on contestable and fair markets in the digital sector and amending Directives (EU) 2019/1937 and (EU) 2020/1828, Art. 6(8) to 6(11).

11 Commission 'Guidelines on the Applicability of Article 101 of the Treaty on the Functioning of the European Union to Horizontal Co-Operation Agreements' (HCG) OJ 2023/C 259/1.

12 Marvin Lee Minsky, *Computation: Finite and Infinite Machines* (Prentice Hall 1967) 23.

13 Gal (2017), 2.

14 See, for example, <https://www.bbc.co.uk/bitesize/guides/zjddqhv/revision/1>.

15 Burton Ong, 'The Applicability of Art. 101 TFEU to Horizontal Algorithmic Pricing Practices: Two Conceptual Frontiers' (2021) 52 IIC 189, 191; Stephanie Assad and others, 'Autonomous Algorithmic Collusion: Economic Research and Policy Implications' (2021A) 37 Oxford Review of Economic Policy 459, 477.

16 Static algorithms are also known as heuristic or expert algorithms; see Emilio Calvano and others, 'Algorithmic Pricing What Implications for Competition Policy?' (2019) 55 Review of Industrial Organisation 155, 158-159; Oxera, *When Algorithms Set Prices: Winners and Losers* (Discussion paper 19 June 2018), 5; Gal (2019), 78.

are used to set prices.[17]

Most algorithms that focus on the use of Big Data are based on machine learning. The UK Competition and Markets Authority ('CMA') has distinguished between three main types of machine learning algorithms,[18] each prone to different market applications: supervised, unsupervised and reinforcement learning. Supervised machine learning departs from a labelled training data set providing examples of similarity and differences (i.e., the correct answers) that the algorithm uses as the basis for regression analysis and classification tasks, such as demand forecasting.[19]

Unsupervised learning lets the algorithm learn a structure from unsorted input data and is helpful in detecting hidden structures and patterns in the data, such as, in a market context, clustering customers according to their willingness to pay.[20]

Reinforcement learning algorithms, such as Q-learning (which we will discuss in Section 4), use a trial-and-error approach changing the input values and observing the outcome of a reward function to maximise the reward.[21] As such, reinforcement learning algorithms optimise their performance, such as setting profit-maximising prices, by experimenting with outcomes that are negative to their current knowledge but that can reveal positive ex-post according to a pre-specified objective.[22] Their functioning features a trade-off between exploring suboptimal actions (i.e., setting new prices) to learn about the environment and exploiting the best action given the current knowledge of the environment (i.e., reverting to a known price).[23]

Deep learning algorithms are a type of machine learning algorithms with multiple layers, also known as deep neural networks. These neural networks are sometimes described as mimicking the brain's cognitive structure.[24] Deep learning algorithms are capable of automatic feature extraction from raw data and have been used in numerous fields for their high accuracy and prediction capabilities. Thanks to their properties, deep learning algorithms can generalise from data they have seen and define features that defy human-readable interpretations to make predictions, outperforming traditional machine learning in applications such as natural language processing, computer vision, or asset pricing.[25]

## *B. Dynamic Pricing Algorithms*

Digital algorithms' two most prominent applications in business are predictive analytics, which is the analysis of Big Data to measure the likelihood of future outcomes, and process optimisation, which is automating tasks to reduce costs and save resources.[26] Among process optimisation algorithms there are dynamic pricing ones, which are in the limelight of competition policy given the transparency and price responsiveness they bring to markets. Dynamic pricing algorithms, also known as repricing algorithms, are a type of pricing algorithms that range from simple rules-based algorithms to complex self-learning algorithms, next to simpler price monitoring algorithms and price recommendation ones.[27] Specifically, dynamic pricing algorithms replace the human decision-maker

17 Joseph Harrington, 'Developing Competition Law for Collusion by Autonomous Artificial Agents' (2019) 14(3) Journal of Competition Law & Economics 331, 342; Assad and others (2021A), 460; OECD (2017), 9.

18 CMA, Pricing Algorithms: Economic Working Paper on the Use of Algorithms to Facilitate Collusion and Personalised Pricing (2018), 11.

19 Ulrich Schwalbe, 'Algorithms, Machine Learning, and Collusion' (2019) 14(4) Journal of Competition Law & Economics 568, 576.

20 Autorité de la Concurrence and Bundeskartellamt (2019), 10.

21 OECD (2023), 9.

22 Emilio Calvano and others (2019), 160.

23 CMA (2018), 11.

24 Ian Goodfellow, Yoshua Bengio and Aaron Courville, *Deel Learning (2016, MIT Press);* OECD (2023), 9.

25 Gal (2017), 5; Ariel Ezrachi and Maurice Stucke, 'Algorithmic Collusion: Problems and Counter-Measures' (OECD, DAF/COMP/WD/(2017)25, 31 May 2017), 23; Autorité de la Concurrence and Bundeskartellamt (2019), 12-13; Luyang Chen, Markus Pelger and Jason Zhu, 'Deep Learning in Asset Pricing' (2023) Management Science 0(0), 54.

26 Gal (2019), 108. CMA, Algorithms: How They Can Reduce Competition and Harm Consumers (2021), 4.

27 Giacomo Calzolari and Philip Hanspach, ´Pricing Algorithms Out of the Box: A Study of the Repricing Industry´, working paper; CMA (2018), 9; OECD (2023), 11; Salil Mehra, 'US v. Topkins: Can Price Fixing Be Based on Algorithms?' (2016) 7 JECLP 470, 472.

in setting prices. Accordingly, they are more likely to raise competition law concerns than price monitoring and recommendation ones that leave price-setting autonomy to firms.[28] Price monitoring software gathers competitor product information for the firm's informed decision-making. In contrast, price recommendation software goes further and suggests the right product price according to a predefined pricing strategy.[29]

Some industries have long delegated their pricing decisions to static algorithms that react to specific circumstances according to lists of prespecified instructions, sometimes called "robo-sellers".[30] This practice, also known as "revenue management" or "yield management", has long aided industries where demand fluctuates much more rapidly than supply, such as the transport and hospitality industry. Nowadays, in any industry, both online and offline sellers increasingly let dynamic algorithms determine prices for their goods leading to higher price fluctuation.[31] Indeed, electronic shelf labels and connected vending machines let brick-and-mortar stores adjust their prices through dynamic algorithms as much as e-commerce merchants do in real time.[32] Any company can replace Excel spreadsheets with affordable repricing software readily available off the shelf from many specialised suppliers or online intermediaries.[33] Although not immune from decision-making mistakes, these complex tools are essential to handle pricing for a large number of products and to remain competitive.[34]

Repricing algorithms pursue a performance objective set by the coder, process data, follow limitations, such as price caps or margin floors, set prices accordingly and adjust these based on data feedback to increase performance.[35] Data inputs can be historical, such as past market trends or individual customers' information; real-time, such as competitors' prices, available stock, weather patterns, production costs or delivery times; or anticipated, such as supply and demand forecasts. Furthermore, the data can be direct, if directly observed, or indirect, if inferred from other data.[36] As to the data sources, firms can collect data in-house through data scraping software or source them from third parties, such as through application programming interfaces or independent intelligence providers.

### *C. The Competitive Facets of Dynamic Pricing Algorithms*

Sellers determine repricing algorithms' objective functions with three possible effects on price and related competition law consequences.[37] A seller can determine that the algorithm should price their products relative to a set of competitors. Indeed, identifying a relevant set of competitors, either within a marketplace or across different websites by drawing on price comparison websites, is an important functionality of these pricing algorithms. On online marketplaces such as Amazon or Bol, a single seller among a group of sellers for a specific product will be presented as the default purchase

28 Oxera (2018), 22.

29 See for example, <https://www.pricefy.io>. Unless stated differently, all websites were last accessed on 1 December 2023.

30 Salil Mehra, 'Antitrust and the Robo-Seller: Competition in the Time of Algorithms' (2016) 204 Minnesota Law Review 1322, 1325.

31 Marco Bertini and Oded Koenigsberg, 'The Pitfalls of Pricing Algorithms' (September-October 2021) Harvard Business Review.

32 See, for instance, https://www.pricer.com/products/digital-price-tags.

33 https://www.minderest.com, https://www.omniaretail.com/dynamic-pricing, https://www.sap.com/italy/products/crm/dynamic-pricing-gk.html https://www.airbnb.com/help/article/1168 See further Footnote 28. For example, pricefy.io subscriptions range from a free account to a premium account for US$ 189 per month, https://www.pricefy.io/#.

34 See, for example, the sale on Amazon of Peter Lawrence's book 'The Making of a Fly' for millions of dollars; https://www.wired.com/2011/04/amazon-flies-24-million/. Zappos.com price cut to $49.95 for all products, https://www.techdirt.com/2010/05/24/zappos-admits-pricing-mistake-cost-it-1-6-million-but-is-upfront-about-taking-the-hit-itself/ ; Uber's 2017 Toronto surge pricing https://www.cnet.com/roadshow/news/uber-charges-toronto-rider-14400-for-a-20-minute-rush-hour-ride/ .

35 Joseph Harrington (2019), 333. One such marketing claim of 1-5% of sales in pure profit through dynamic pricing; https://www.digitalcommerce360.com/2019/10/03/online-pricing-horror-stories-and-how-to-avoid-becoming-the-next-victim/.

36 Hubert Bekisz, 'When Does Algorithmic Pricing Result In an Intra-Platform Anticompetitive Agreement or Concerted Practice? The Case of Uber in the Framework of EU Competition Law' (2021) 12 JECLP 217, 219; CMA (2018), 15; Cary Coglianese and Alicia Lai, 'Antitrust by Algorithm' (2022) 2 Stanford Computational Antitrust 1, 2; Francisco Beneke and Mark-Oliver Mackenrodt, 'Remedies for Algorithmic Tacit Collusion' (2021) 9 Journal of Antitrust Enforcement 152, 155.

37 Ong (2021), 191-192; Autoridade de Concorrência (2019), 50.

option. Amazon calls this the “Buy Box”.[38] Since most sales go through the Buy Box, many pricing algorithms advertise themselves as helping sellers win it.[39] Furthermore, being the cheapest seller is an important determinant in winning the Buy Box, so undercutting rivals is the most common application of repricing algorithms. This should be seen as fully pro-competitive unless the price is below cost predatorily. Combined with constraints on the price setting that preserve minimum margins and reset to high prices once prices have dropped below a predetermined threshold, pricing algorithms can lead to price cycles with ambiguous effects on overall prices.

Alternatively, they may price above market average prices, for example, to protect a brand’s luxury image. In a vertical e-commerce context, suppliers could impose premium pricing objectives on distributors to enforce resale-price maintenance schemes.[40] Last, algorithms may price around market average prices to optimise the trade-off between higher prices and lower sales,[41] maximising turnover and profitability, which in a horizontal context could lead to follow-the-leader pricing patterns and, possibly, to collusion.

Several factors can affect the behaviour of repricing algorithms and so their impact on competition. These factors are both internal to the sellers employing the algorithms, such as the code or training data used, and external, such as the market context where the algorithms operate.[42] Due to the uncertain competitive effect, presumptions of unlawfulness against pricing algorithms risk a chilling effect on welfare-enhancing practices, commending a case-by-case analysis.[43] Focusing on the benefits, repricing algorithms are a powerful tool to extract value from Big Data that can foster market transparency and efficiencies.[44] On the one hand, they enable fast and accurate analysis of large amounts of data and so increase market transparency, which in turn reduces information asymmetries.[45] More market information enables informed decision-making and benchmarking, enhances trust, reduces search costs and price dispersion and facilitates planning for both suppliers and consumers. On the other hand, they can enhance both static and dynamic efficiencies.

First, repricing algorithms might enable productive efficiency through cost reductions and avoided agency slack: after an initial investment, they reduce the human labour needed to set prices and reduce the likelihood of human errors in the price-setting process. Simple and cheap price-setting processes can even facilitate entry by new suppliers that can learn about markets, freeride on the incumbents’ pricing data and set up shop quickly.[46] Such cost reductions can translate into lower prices for consumers, too.

Second, repricing algorithms enable real-time accurate price adjustments and personalised prices that spur allocative efficiencies. They also reduce waste by promoting the equilibrium between supply and demand. In other words, by guaranteeing constant market equilibria, dynamic pricing can prevent unsatisfied demand and excess supply, favouring sustainable business. For example, repricing algorithms can increase stock turnover and minimise storage fees.

38 The way Amazon decides which product offers will be featured in the “Buy Box” has been central to several abuse of dominance cases in Europe: see Italian Competition Authority case no. A528 *FBA Amazon, infringement decision n. 29925 of 30 November 2021; Commission Decision 20 December 2022 (Case AT.40703) Amazon – Buy Box C(2022) 9442 final; CMA Case 51184, Amazon Marketplace, Notice of intention to accept commitments 26 July 2023.*

39 See further fn 28

40 Resale-price maintenance via price monitoring software was at issue in the *Asus Consumer Electronics case, see* Commission Decision 24 July 2018 (Case AT.40465) *Asus* C(2018) 4773 final para. 27.

41 CMA (2018), 14.

42 Niccolò Colombo, ‘Human Liability Vis-à-vis Artificial Intelligence’s Anticompetitive Behaviours’ (2018) 1 CoRe 11, 12; Stefan Thomas, ‘Harmful Signals: Cartel Prohibition and Oligopoly Theory in the Age of Machine Learning’ 15(2-3) Journal of Competition Law & Economics 159, 198.

43 Gal (2019), 111.

44 Note that transparency for sellers can also facilitate collusion; Gal (2023), 196.

45 HCG, para 373.

46 Oxera (2018), 2.

Finally, repricing algorithms might also support dynamic efficiency in the form of product and business model innovation. Arguably, a specific type of repricing algorithm, that is ads auction algorithms, is behind much of the digital economy by enabling a business model of free access to many innovative online services in exchange for personalised advertisement.[47] At the same time, dynamic pricing enables the sharing economy where digital platforms put a price on almost any peer-to-peer exchange, starting from Airbnb accommodations and Uber rides.[48]

However, the same technological properties behind the benefits of algorithmic pricing, above all the analytical capabilities, can lead to unilateral and multilateral anti-competitive effects. Unilaterally, repricing algorithms can exploit the behavioural biases of consumers, such as loss aversion or social proof, reach perfect price discrimination, tilting surplus towards suppliers,[49] and foreclose competitors with predatory pricing strategies. Multilaterally, they can support or even establish collusion, which is the focus of the next section.

## 3. Algorithmic Collusion Between EU Law and Economics

### *A. Collusion Under Art. 101 TFEU Focusing on Concerted Practices*

Before delving into algorithmic collusion, it is necessary to clarify the concept of collusion since lawyers and economists employ it differently. From the EU competition law perspective, collusion carries a pejorative meaning referring to multilateral coordinated behaviour with anti-competitive objects or effects and, therefore, infringing Art. 101(1) TFEU. Leaving aside decisions of association of undertakings, the EU prohibition of collusion encompasses a spectrum of anti-competitive coordination that goes from more or less explicit agreements between firms, such as price-fixing cartels, to informal concerted practices, such as sensitive information exchanges.[50] The boundary between agreements and concerted practices is imprecise on purpose, and this flexibility of Art. 101(1) TFEU is especially useful vis-à-vis innovative methods of anti-competitive coordination, including through pricing algorithms. Indeed, EU law deters coordinated anti-competitive practices regardless of the means of implementation against circumvention strategies. To that end, a formal restrictive contract is subject to the exact subjective requirements, fines and remedies of informal concerted practice.[51] The critical difference between the two multilateral anti-competitive practices lies in their objective requirements and so on how they manifest themselves and hence are evidenced.

The EU case law on the meaning of agreement identifies the concept around the “concurrence of wills” between undertakings to implement a common intention,[52] regardless of the validity and binding effect of the underlying obligations under national law.[53] Such a concurrence of wills is shown to exist by evidence of an offer and acceptance, be it explicit or inferred from conduct in the market.[54] As expanded in sub-section C. below, the notion of agreement does not apply to algorithmic collusion lacking any meeting of human minds. It is applicable only when pricing algorithms are the means to implement or strengthen a pre-existing anticompetitive agreement. Instead, the looser notion of concerted practices is more useful against collusion by algorithms. Since the seminal *Dyestuffs* case of 1972, a concerted practice may exist where, without any clear-cut agreement, firms knowingly

47 Oxera (2018), 32.

48 Dan Hill, ‘The Secret of Airbnb’s Pricing Algorithm’ (20 August 2015, IEEE Spectrum); Jessica Phillips, ‘How Uber’s Dynamic Pricing Model Works’ (21 January 2019, Uber Blog).

49 Arguably, pricing of personalised goods is more likely based on consumers’ characteristics than on the market environment and therefore less amenable to collusion than homogeneous goods markets; see Schwalbe (2019), 572; CMA (2021), 8-9 and 22.

50 HCG, paras 366 ff.

51 Council Regulation (EC) No 1/2003 of 16 December 2002 on the implementation of the rules on competition laid down in Articles 81 and 82 of the Treaty, OJ (2003) L1/1, Arts. 7(1), 23(2) and 24.

52 C-2 and 3/01 P *Bundesverband der Arzneimittel-Importeure v Bayer* EU:C:2004:2, para 97, quoting the first instance judgment Case T-41/96 *Bayer v Commission* EU:T:2000:242, paras 69 and 173.

53 Case 41/69 *ACF Chemiefarma v Commission*, para 111-113; C-277/87 *Sandoz Prodotti Farmaceutici v Commission* EU:C:1990:6 (Summary publication), para 2.

54 C-48/69 *ICI v Commission* EU:C:1972:70, paras 104 and 109.

substitute practical cooperation between them for the risks of competition.[55] There, the Commission fined ten chemical companies controlling most of the European dyestuffs market for three uniform and simultaneous price increases for the same range of products between 1964 and 1967 upon evidence of advance price announcements and industry meetings.[56]

In practice, unlawful concertation consists of direct or indirect contact, for example, unilateral disclosures of sensitive information, whose object or effect is to influence the conduct of rivals or to disclose one's course of conduct[57] without any plausible explanation other than restricting competition.[58] For example, in the *Wood Pulp II* case, the parallel price announcements by Scandinavian and US wood pulp producers were not a concertation. Instead, they naturally stemmed from the oligopolistic tendencies of both sides of the relevant market and its cyclical nature.[59] Importantly, negligence suffices to breach Art. 101(1) TFEU, so the fact that the contact lacks an anti-competitive intent does not exclude its unlawfulness insofar as it reduces the uncertainty that otherwise would exist in the market.[60]

Further, suppose coordinated market conduct follows even a single concertation instance, such as the one meeting in *T-Mobile Netherlands*. In that case, EU law rebuttably presumes a causal link between the contact and the conduct.[61] Similarly, undertakings that participated in a concertation and continue operating on the market are assumed to have considered contact with their competitors for their subsequent course of action.[62] Such presumptions reverse the burden of proof, resting on the parties to adduce evidence refuting any causal link between the contact and subsequent parallel conduct. In this sense, passive information recipients bear liability unless they publicly distance from the coordinated behaviour, report it to the authority, disregard the information as a maverick or prove a lack of knowledge.[63]

Notably, parallel behaviour that results from the independent and rational adaptation of each firm's conduct on the market, that is, conscious parallelism or the oligopoly problem, is outside the scope of Art. 101(1) TFEU.[64] The freedom to conduct a business and the right to property, respectively recognised by the Arts. 16 and 17 of the EU Charter of Fundamental Rights,[65] guarantee that unilateral actions corresponding to the rational adaptation to market forces are lawful even if they lead to coordination in a repeated prisoner's dilemma.[66] Furthermore, any remedy against conscious parallelism would risk forcing firms to act irrationally, pretending not to know the interdependency of their actions.[67] Without proof of the existence of concurrence of wills behind agreements or contacts behind concerted practices, EU law does not prevent competitors from reacting unilaterally to existing or anticipated market circumstances.[68] The only boundary to the oligopoly problem is the abuse of a dominant position in a relevant market under Art. 102 TFEU. At the same time, merger control prevents oligopoly problems by ensuring that no structural market change increases the likelihood of future coordinated behaviour that might otherwise escape the Art. 101(1) TFEU prohibition.

55 *ICI v Commission*, paras 64-65.

56 *ICI v Commission*, paras 91-92, 100-102.

57 C-40/73 *Suiker Unie v Commission* EU:C:1975:174, paras 26 and 174.

58 Joined Cases C-89/85, C-104/85, C-114/85, C-116/85, C-117/85 and C-125/85 to C-129/85 *Ahlström Osakeyhtiö and others v Commission (Wood Pulp II) EU:C:1993:120, para 71;* C-74/14 *Eturas*, EU:C:2016:42, paras 36-37.

59 *Wood Pulp II*, paras 126-127.

60 On the irrelevance of intent for competition law infringements, see C-67/13 P *Cartes Bancaires v Commission* EU:C:2014:2204, para 54; Jan Blockx, 'Artificially Intelligent Collusion Caught Under EU Competition Law' in Steven Van Uystel, Salil Mehra and Yoshiteru Uemura (eds) *Algorithms, Collusion and Competition Law (Eward Elgar, 2023), 55.*

61 C-8/08 *T-Mobile Netherlands* EU:C:2009:343, paras 51-53.

62 C-199/92 P *Hüls v Commission* EU:C:1999:358, paras 161-163.

63 *Eturas*, paras 44-47.

64 Thomas (2019), 166.

65 Charter of Fundamental Rights of the European Union OJ 2016 C 202/389.

66 C-609/13 P *Duravit v Commission* EU:C:2017:462, para 72.

67 Gal (2023), 201; Thomas (2019), 189.

68 Suiker Unie v Commission, paras 173-174.

### *B. Collusion in Economics and the Impact of Pricing Algorithms*

In economics, collusion refers to coordinated market behaviours that lead to supra-competitive prices. Price-fixing is its most emblematic type, although collusion may concern other competitive parameters, such as quantity, quality, market segmentation or innovation. Such an artificial restriction of competition is possible thanks to a collective exercise of market power that raises profits and reduces consumer welfare. Economists, considering the means to reach collusion, distinguish between explicit collusion based on communication between firms and tacit collusion where communication is missing, and firms reach coordination individually thanks to the rational adaption to their interdependent actions. As such, anti-competitive agreements and concerted practices fit the concept of explicit collusion, while tacit collusion corresponds to the oligopoly problem of parallel behaviour that escapes competition law liability.

At the core, collusion consists of a reward-punishment scheme.[69] Preliminarily, market participants must reach a common understanding toward a collusive equilibrium, the so-called focal point, that is profitable and rewards all parties.[70] To that end, they must perceive the interdependency of each other's actions. Then, the colluding firms must be able to discover defections from the collusive equilibrium swiftly and punish deviating firms effectively. Such enforcement structures enhance the internal stability of collusion and diminish each firm's otherwise strong incentive to deviate from the collusive equilibrium to achieve short-term benefits unilaterally.[71] In other words, firms must be aware that coordination is in the common interest and that cheating via unilateral price cuts will cause a severe price war that will hurt their profit. The common understanding and the enforcement structures of collusion are unlikely absent communication between the parties or circumstances relating to market structure and supply and demand features.

Market concentration, entry barriers, transparency and frequent interactions are among the structural market characteristics that ease collusion.[72] First, convergence toward focal points is easier in oligopolies of a few firms with similar market shares than in atomised markets with many asymmetric firms employing different business models.[73] Oligopolies also facilitate collusion because the transaction cost to agree and maintain the coordination is limited, while the shares of supra-competitive gains for each firm are large.[74] Second, market entry barriers enhance collusion's external stability, protecting it against potential competitors. Third, industry awareness and visibility of each player's behaviour allows for monitoring and detection of deviations.[75] Last, frequent interactions ease communication and signalling of focal points and enforcement schemes. They also make deviations from the collusive equilibrium less profitable and punishment threats more credible than markets subject to isolated and far-apart transactions.

Supply and demand features also affect the likelihood of collusion. From the supply side, asymmetric supply costs due, for example, to differences in production processes or to different degrees of vertical integration, and product differentiation due, for instance, to quality, innovation, personalisation or brand loyalty, impair collusion. In contrast, cost symmetries and homogeneous products make reaching a common understanding over a focal point easier.[76] From the demand side, growing demand enhances the internal stability of collusion because firms have a smaller incentive to cheat for lower profits today vis-à-vis large collusive profits tomorrow. Instead, volatile demand because of unforeseen situations or unstable business cycles impairs collusion since firms can cheat

69 George Stigler, 'A Theory of Oligopoly' (1964) 72 Journal of Political Economy 44; Harrington (2019), 336.
70 Autorité de la Concurrence and Bundeskartellamt (2019), 16.
71 OECD (2017), 19; CMA (2018), 43.
72 Autorité de la Concurrence and Bundeskartellamt (2019), 17.
73 Schwalbe (2019), 592.
74 Gal (2019), 75.
75 Antonio Capobianco and Pedro Gonzaga, 'Algorithms and Competition: Friends or Foes?' (August 2017) CPI Antitrust Chronicle, 2.
76 Oxera (2018), 23; Schwalbe (2019), 570; CMA (2021), 29.

when demand is high and reduce the cost of retaliation at lower peaks.[77]

Now, add algorithmic pricing to the general economic theory of collusion. Its adoption by suppliers impacts each structural market characteristic positively, enabling coordination beyond traditional oligopolies. In addition, the complex problem-solving capabilities of repricing algorithms and the substantial transparency of digital markets on data of consumers and rivals could reduce the obstacles to collusion posed by supply and demand factors such as product differentiation, multi-product pricing, supply-cost asymmetries and demand fluctuations.[78] The analytical power, speed and accuracy of algorithmic pricing can facilitate common understanding among competitors and strengthen enforcement structures outside concentrated and transparent markets. Such properties also make pricing algorithms a competitive advantage for the colluding firms, increasing both the internal and external stability of collusion: pricing algorithms can constitute a fast and precise detection and punishment scheme against cheaters and an entry barrier to foreclose new entrants, destabilising the coordinated equilibrium.[79] Further, pricing algorithms discourage entry insofar as the most performant analysis tools are accessible to the incumbents only due to costs or computing power needs.

Thanks to accurate analytics, it has been argued that repricing algorithms might better distinguish deviations from a collusive price between those aimed to undercut the collusive price, those due to changed market circumstances and those due to mere mistakes.[80] In this sense, they could quickly retaliate against sellers that "cheat" during a phase of collusion and avoid price wars in other cases.[81] Further, real-time price reactions raise the frequency of interactions. They might so facilitate not only the initial common understanding over focal points[82] but also the monitoring of deviations, their punishment and the re-establishment of collusion. Moreover, the faster pricing algorithms can detect and punish deviations, the less profitable deviation from a collusive agreement is.[83]

Not least, pricing algorithms, being readable and predictable by actual and potential market participants, who can observe them in action and even rely on their encoded course of action, can reduce uncertainty and increase trust among colluding firms and disincentivise new entrants.[84] Indeed, pricing algorithms can put rivals on notice regarding future decisional parameters, the frequency of input collection and the corresponding punishment. In other words, if correlations between pricing inputs and outputs are observable, then prices become predictable, making algorithms both a vehicle of collusive signal and a self-commitment device for cartelists.[85] Finally, pricing algorithms facilitate collusion by overcoming human limitations in decision-making. Compared to humans, algorithms are free from detection fear, lack a sense of wrongdoing, and can avoid human biases.[86]

77 Autorité de la Concurrence and Bundeskartellamt (2019), 16; Beneke and Mackenrodt (2021), 155.

78 Thomas (2019), 167.

79 Gal (2023), 184-185; Ariel Ezrachi and Maurice Stucke, 'Algorithmic Tacit Collusion' in Peter Whelan (ed), *Research Handbook on Cartels* (Edward Elgar, 2023), 191-192.

80 OECD, Algorithms and Collusion (2017, OECD Background note DAF/COMP(2017)4), 20.

81 CMA (2018), 23-24.

82 Michael Coutts, 'Mergers, Acquisitions and Algorithms in an Algorithmic Pricing World' (2022) SSRN-id4044937, 19-20.

83 Oxera (2018), 9; Ezrachi and Stucke (2023), 192.

84 Beneke and Mackenrodt (2021), 163.

85 Gal (2019), 86-87.

86 Pricing algorithms could hide coordination by generating price heterogeneity when there is no demand while maintaining coordination overall or concealing information exchanges behind encryption; Ezrachi and Stucke (2023), 193; Thomas (2019), 167; Autorité de la Concurrence and Bundeskartellamt (2019), 28. Without human intervention, individual employees cannot undermine the algorithmic cartel; CMA (2018), 23-24.

## C. Algorithmic Collusion Theories of Harm

Ezrachi and Stucke are among the first to frame the risks of algorithmic pricing collusion.[87] They distinguish four algorithmic collusion theories of harm: Messenger, Hub and Spoke, Predictable Agent and the Digital Eye.[88] The first two scenarios relate to using repricing algorithms as a technology that implements or strengthens collusion. As such, they are the least problematic for EU competition law since the use of any technology better to implement a pre-existing anti-competitive agreement or concerted practice does not change the unlawfulness of the underlying conduct under Art. 101(1) TFEU.[89] The third scenario refers to pricing algorithms as enablers of collusion, whereas the last scenario predicts the establishment of tacit collusion by autonomous algorithms reacting to each other.[90] Under strict conditions relating to the type of information embedded in the algorithm and competitors' awareness, the third scenario could fit the analysis of anticompetitive information exchanges, as revamped by the 2023 Horizontal Cooperation Guidelines.[91] Instead, absent evidence of direct or indirect contact between firms, that is, of concertation, the last scenario challenges the application of Art. 101(1) TFEU and can constitute an enforcement gap under EU competition law.

In the Messenger constellation, repricing algorithms build upon an antecedent anti-competitive agreement. Pursuing a follow-the-leader objective function, the algorithm can detect and respond to pricing deviation easily, quickly and with effective tit-for-tat strategies, making explicit collusion more stable.[92] As the 2023 Horizontal Cooperation Guidelines recognise, collusion by code on essential competition parameters is typically a restriction by object.[93] Actions by a pricing algorithm under a firm's control are tantamount to actions by employees or consultants that can determine the firm's liability.[94]

The 2016 *Trod* case in the UK is the classic example of the Messenger scenario: a horizontal price-fixing cartel documented by extensive written communication between the firms and implemented using repricing algorithms.[95] Upon a leniency application, the Competition and Markets Authority found that two competitors selling posters and frames on Amazon marketplace unlawfully agreed from 2011 and 2015 to monitor and adjust their prices to avoid price wars.[96] After facing hurdles in executing the agreement, the cartelists implemented their anti-competitive scheme using two repricing algorithms provided by different software providers.[97] Specifically, the algorithms were designed to undercut the prices for competing products by a certain percentage, except those competitors added to an "ignore" list, overriding the general rule.[98]

The second Hub and Spoke scenario involves different competitors, the spokes, using in parallel, without direct communication, the same repricing algorithm provided by a third party, the hub. In such a situation, the software provider serves as a ringleader that, through the algorithm, coordinates directly the spokes' prices (i.e., code-level coordination) or indirectly sensitive information exchanges among them (i.e., data-level coordination). If the provider's remuneration depends on the performance of

87 Ezrachi and Stucke (2016).

88 Ezrachi and Stucke (2016), 35-71.

89 The FTC chairman reportedly quipped that "algorithm" in this case may just as well have been "a guy named Bob", see Maureen Ohlhausen, *Should We Fear The Things That Go Beep In the Night? Some Initial Thoughts on the Intersection of Antitrust Law and Algorithmic Pricing (23 May 2017 Remarks from the Concurrences Antitrust in the Financial Sector Conference);* Gal (2023), 209; Thomas (2019), 169.

90 Bekisz (2021), 221.

91 HCG, Section 6 Information Exchange.

92 Thomas (2019), 169; Assad and others (2021A), 461.

93 HCG, para 379.

94 C-68/12 *Slovenská sporitelna EU:C:2013:71, para 25;* Luca Calzolari, 'The Misleading Consequences of Comparing Algorithmic and Tacit Collusion: Tackling Algorithmic Concerted Practices under Art. 101 TFEU' (2021) 6 European Papers 1193, 1219.

95 CMA (2018), 22. The Trod case had a US parallel case always involving collusion via algorithms by poster seller on Amazon Marketplace, see Plea Agreement, *United States v. David Topkins* [30 April 2015]; Information, *United States v. David Topkins* [6 April 2015]; Salil Mehra, '*US v. Topkins*: Can Price Fixing Be Based on Algorithms?' (2016) 7 JECLP 470.

96 CMA Case 50225, *Online Sales of Posters and Frames decision of 12 August 2016, para 1.3.*

97 Ibid, para 3.46.

98 Ibid, paras 3.62. - 3.93.

the pricing software, it might even have an incentive to generate supra-competitive prices through collusion between its clients.[99] Further, the risk and impact of collusion are higher if a single algorithm is applied on a large scale as an industry standard,[100] while it is lower if multiple suppliers compete in the design and supply of pricing software.[101]

Following the *AC-Treuhand* judgment, the software supplier could be liable as a cartel facilitator if its conduct contributes to the negotiation, monitoring and implementation of its clients' overt anti-competitive agreement.[102] Like *AC-Treuhand*, the consultancy firm that infringed Art. 101(1) by organising and attending its clients' cartel meetings, providing sales data and mediating their disputes, the third-party software supplier can be the intermediary that facilitates the anti-competitive agreement. Vice versa, a firm sourcing its pricing algorithm from a software supplier cannot be automatically liable for this latter's anti-competitive acts.[103] This results from the *VM Remonts* case, where a firm participated in a public tender using the services of a consultant without knowing that the same consultant worked for the two other bidders and coordinated all submissions.[104] For the CJEU, a firm's indirect liability for a contractor's breach of Art. 101(1) TFEU can only arise in three alternative exceptional circumstances: 1) the contractor was actually dependent on the firm that used its services; 2) the firm was aware of the anti-competitive coordination in place between its competitors and the contractor and intended to contribute to it by its own conduct; 3) the firm could have reasonably foreseen such coordination and accepted the risks of infringement.[105] Therefore, absent awareness or negligence, a firm using a third-party pricing algorithm can avoid liability for the hub and spoke collusion occurred between a totally independent software provider and the firm's competitors.

The third Predictable Agent scenario refers to pricing algorithms as enablers of collusion insofar as firms can read each other's software codes, including their code-embedded future course of action, replacing decision-making transparency for strategic uncertainty in the market.[106] Without human intervention other than the coders, firms consciously or negligently can signal if, when and how prices have changed and will change by reacting to different market circumstances. Every market participant can become aware of the others' past and future likely reactions to one's actions, similar to price matching guarantees that decrease the competitive pressure of undercutting prices to increase demand, market shares and profits.[107] Accordingly, the pricing algorithm can function as a unilateral commitment to collude and an explicit threat of retaliation for discounters.[108] In particular, the algorithms can be coded to be harder to change, strengthening the degree of reliance on them by competitors like long-term price commitments and credible price wars.[109]

Liability for the firm deploying the predictable pricing algorithm would depend on the type of information embedded in the code and its accessibility.[110] However, disclosure of granular data on past price adjustments and the firm's future pricing strategy can hardly have any plausible explanation other than reducing market uncertainty and paving the way to anti-competitive coordination.[111] Regarding the accessibility of the information, a firm could avoid responsibility if competitors unilaterally obtain commercially sensitive data through reverse-engineering of an encrypted pricing algorithm.[112] In

99 Autorité de la Concurrence and Bundeskartellamt (2019), 32-33.
100 CMA (2021), 7.
101 Schwalbe (2019), 573; Matthias Hettich, 'Algorithmic Collusion: Insights from Deep Learning' (2021) Center for Quantitative Economics WP n. 94/2021, 16.
102 C-194/14 P *AC-Treuhand* EU:C:2015:717, paras 36-39.
103 Autorité de la Concurrence and Bundeskartellamt (2019), 36.
104 C-542/13 *VM Remonts* EU:C:2016:578, para 25.
105 *VM Remonts*, paras 27, 29 and 31.
106 Gal (2023), 184-185.
107 Schwalbe (2019), 574.
108 Oxera (2018), 18; Thomas (2019), 169.
109 Gal (2019), 111.
110 HCG, paras 384 ff.
111 HCG, paras 396 ff.
112 HCG, paras 406-411.

contrast, adopting straightforward and transparent pricing algorithms that competitors can easily access can more likely lead to anticompetitive information exchanges.

As a potential example of predictable agents algorithmic collusion, the Italian Competition Authority opened an investigation under Art. 101 TFEU over the allegedly anti-competitive price increase of flights between continental Italy and Sicily during Christmas 2022.[113] The Authority acknowledges that dynamic pricing by airline companies is the industry standard.[114] However, it notes that the price increase could result from collusion between airlines "possibly facilitated by the use of pricing algorithms" rather than a rational adaptation to market conditions. As *prima facie* evidence of collusion, it highlights the abnormal alignment of prices and lack of other pro-competitive and profit-maximising initiatives that would meet the demand.[115] In parallel, the Authority also opened a sector inquiry into airlines' use of pricing algorithms.[116]Furthermore, the *Eturas* case clarifies firms' liability at the receiving end of collusion through predictable agents. For the CJEU, the information recipient's liability for a concerted practice arises from the mere awareness of commercially sensitive information received from a competitor unless such a firm undertakes any public action that disavows the content of the information.[117] There, the Lithuanian Competition Council fined E-Turas and thirty travel agencies for applying a common cap on discounts applicable to services provided through the E-Turas online booking platform.[118] The discount cap was communicated to the agencies through an internal messaging system as an amendment to the platform terms and conditions and then implemented by E-Turas technically.[119] Upon referral by the Lithuanian appeal court, the CJEU held that objective and consistent indicia may justify a rebuttable presumption of awareness once communication has been issued.[120] Arguably, firms that monitor competitors' prices might be presumed to be aware of their competitors' predictable agents.

The last and most extreme scenario is the Digital Eye.[121] Here, firms without contact with each other use different pricing algorithms that autonomously learn to collude. The concern is that self-learning repricing algorithms accessing similar data and instructed with similar goals might identify coordinated outcomes as an optimal profit-maximising strategy, even in dynamic market contexts.[122] In other words, after many possible interactions, the pricing algorithms can learn they are interdependent and that undercutting other firms' prices brings forth a price war with low profits that ultimately makes deviation from the coordinated price unprofitable.[123]

Lacking human intervention or actual information sharing, autonomous collusion by pricing algorithms may amplify the oligopoly problem by expanding the grey area between unlawful explicit collusion and lawful tacit collusion.[124] The antitrust loophole could even contribute to more stable collusive outcomes: knowing that self-learning algorithms escape liability for tacit collusion, firms have incentives to adopt similar algorithms without diversifying their design.[125] Absent a legal precedent,

113 Italian Competition Authority case no. I863 *Flight ticket prices from and to Sicily during Christmas, decision opening an investigation n. 30408 of 20 December 2022.*

114 Ibid, para 18.

115 Ibid, para 19.

116 Italian Competition Authority case no. IC56 *Sector investigation into pricing algorithms in passenger air transport for routes to and from Sicily and Sardinia, decision opening an inquiry of 6 November 2023. If the sector inquiry leads to anticompetitive findings, the authority may even impose structural or behavioural remedies thanks to sector-specific legislation on the transparency of flight ticket prices, see Art. 1 Legislative Decree n. 104/2023.*

117 *Eturas*, paras 28, 41 and 44.

118 *Eturas*, paras 19-21.

119 *Eturas*, paras 10-11.

120 *Eturas*, para 41.

121 Pieter Van Cleynenbreugel, 'Article 101 TFEU's Association of Undertakings Notion and Its Surprising Potential to Help Distinguish Acceptable from Unacceptable Algorithmic Collusion' 2020 65 Antitrust Bulletin 423, 427-28; Ariel Ezrachi and Maurice Stucke, 'Artificial Intelligence & Collusion: When Computers Inhibit Competition (2017) 68 University of Illinois Law Review 1775, 1790.

122 OECD (2023), 13; Oxera (2018), 17; CMA (2018), 48-49.

123 Assad and others (2021A), 466; Autorité de la Concurrence and Bundeskartellamt (2019), 21.

124 Giuseppe Colangelo and Francesco Mezzanotte, 'The Evolving (?) Notion of 'Agreement' in the Age of Algorithms. Interaction Between Antitrust and Contract Law' (2022) 1 Roma Tre Law Review 47, 51.

125 Thomas (2019), 184.

economists and computer scientists tested whether algorithms could autonomously collude and looked for empirical evidence, as reviewed in the following Section.[126]

## 4. Studying the Effects of Pricing Algorithms in Online Markets

The literature that studies the effects of algorithmic pricing is conveniently summarised with a joint methodological and chronological approach. First, there is literature preceding the debate on algorithmic collusion. This research either analyses the features of dynamic pricing algorithms from a computer science perspective or looks for new computational approaches to simulate economics models (Sub-section 4.A.). The current wave of economics literature started after legal scholars speculated about the abovementioned algorithmic collusion theories of harm. Here, there are two strands of research: one of simulations and computational methods that analyses the conditions for coordination through algorithms (Sub-section 4.B.), the other of experimental and empirical methods that focuses on the human-machine interaction (Sub-section 4.C.)

### *A. Algorithmic Pricing Before and Besides the Debate on Collusion*

The economics discussion of algorithms for pricing precedes the policy-driven discussion of algorithms in marketplaces by at least a decade. Already Tesfatsion describes the need to define algorithmic pricing rules for agents in computational representations of economies.[127] This agent-based modelling (ABM) approach aims to study the emergent behaviour of economic agents, not to compare differential pricing outcomes between algorithmic and conventional pricing. While these papers do not take an explicit stance on competition policy, they incorporate aspects that have received little attention in the industrial organisation literature, such as buyer-seller interaction and bounded rationality.

Studying electricity markets, Barazza and Strachan employ pricing algorithms that account for bounded rationality on the side of producers whose decision algorithms determine production and implicit prices and a government that algorithmically sets a CO2 price to achieve emissions targets, reacting to firm decisions.[128] Filatova, Parker, and Veen demonstrate the use of a simple pricing algorithm in ABM to study price formation on land markets.[129] Here, buyers and sellers adjust their prices starting from their reservation prices by a gradient determined by the relative size of the buyer and seller population. While mechanical, this use of pricing algorithms in ABM also incorporates buyer-seller interaction while considering bounded rationality (albeit in the unsatisfactory way of simply ignoring expectations). As argued below, a gap in the literature on algorithmic repricing is precisely the reaction of buyers to the pricing patterns induced by algorithms which can be found in this earlier literature, even if it is just rudimentary.

Boer surveys the earlier literature on dynamic pricing, including price formation and statistical learning, covering computer science, management, operations research, and economics literature.[130] However, the discussion of the economics literature and competition is limited to general questions of price formation and less on how the use of pricing algorithms by economic agents impacts price formation in markets.

126 Nicolas Petit, 'Antitrust and Artificial Intelligence: A Research Agenda' (2017) 8 JECLP 361.

127 Leigh Tesfatsion, 'Agent-Based Computational Economics: A Constructive Approach to Economic Theory' in Leigh Tesfatsion and Kenneth Judd (eds), *Handbook of Computational Economics Vol. 2* (Elsevier 2006).

128 Elisa Barazza and Neil Strachan, 'The Co-Evolution of Climate Policy and Investments in Electricity Markets: Simulating Agent Dynamics in UK, German and Italian Electricity Sectors' (2020) 65 Energy Research and Social Science.

129 Tatiana Filatova, Parker Dawn and Anne van der Veen, 'Agent-Based Urban Land Markets' (2009) 12 Journal of Artificial Societies and Social Simulation 31.

130 Arnoud van den Boer, 'Dynamic Pricing and Learning: Historical Origins, Current Research and New Directions' (2015) 20 Surveys in Operations Research and Management Science 1.

To some degree, the discussion on algorithmic collusion can be seen as a strand of the literature on repeated games. The Folk theorem states that there is potentially a large number of equilibria that can be supported in repeated play with patient players.[131] These equilibria include outcomes that could be called "competitive" or "collusive" equilibria in some settings, as well as any number of intermediate outcomes.[132]

While this literature saw the most activity in the 80s and early 90s, possible refinements and equilibrium-selection procedures for repeated games are still discussed today. When restrictive features of algorithms are assumed (such as a memory of specific length in some of the computational literature discussed in the following sub-section), papers that study algorithmic collusion are essentially looking for the equilibria that emerge under specific learning protocols and restrictions. Researchers investigating algorithmic collusion should, therefore, explain whether the restrictions of their algorithms that allow equilibrium selection should be taken as exogenous and fixed (for example, due to technical reasons) and, if not, whether any equilibria that emerge are robust to perturbations (for example, the introduction of a new algorithm with a longer memory, faster reaction etc.)

The literature on repeated games has also long studied finite automata, namely models of computation used to recognise patterns in an input string.[133] These can be considered relevant as an algorithm is a finite sequence of instructions to solve a calculation or problem. A pricing algorithm is no different. Recent papers have also made direct applications to algorithmic repricing. Notably, Dal Bó and Fréchette experiment with repeated prisoner's dilemma under perfect monitoring and discuss the recovery of strategy from observed actions, a setting that could apply to algorithms that monitor competitors' prices in marketplaces.[134]

### *B. Speculative and Theoretical Literature*

Companies typically do not reveal their pricing strategies to keep a competitive advantage and to comply with antitrust rules. Researchers, therefore, either study simple algorithms in a simulated environment or draw inference from observable characteristics of pricing data (such as the frequency of price changes) to make an educated guess about the presence of pricing algorithms in observational data. This sub-section looks at cases of the former.

The simulation literature studies the behaviour of certain algorithms in stylised oligopoly models. Calvano and others analyse a particular type of reinforcement learning algorithm, that is Q-learning[135], in a repeated Bertrand setting with simultaneous updating, while Klein studies a similar problem with sequential updating.[136] Both papers find that, in controlled setups, the algorithmic agents set prices above the "competitive price" associated with the static Nash equilibrium of the stage game. Importantly, this price setting is supported by a collusive strategy that involves punishing deviations from the collusive price by a price cut, followed by gradual readjustment to higher prices. In other words, the reward-punishment schemes occurred as emergent properties in multi-agent learning.

131 Drew Fudenberg and Eric Maskin, 'The Folk Theorem in Repeated Games with Discounting or with Incomplete Information' (1986) 54 Econometrica 533.

132 Andrzej Skrzypacz and Hugo Hopenhayn, 'Tacit Collusion in Repeated Auctions' (2004) 114 Journal of Economic Theory 153.

133 Dilip Abreu and Ariel Rubinstein, 'The Structure of Nash Equilibrium in Repeated games with Finite Automata' (1988) 56 Econometrica 1259.

134 Pedro Dal Bó and Guillame Fréchette (2019), "Strategy Choice in the Infinitely Repeated Prisoner's Dilemma". In: American Economic Review 109.11, pp. 3929–3952.

135 Q-learning can be defined as a model-free implementation of reinforcement learning in which a matrix of payoffs for actions in different states is updated after each action that was taken. The decision maker varies between taking the predicted best action or choosing a random action to allow for experimentation and learning, starting from arbitrary initial payoff matrices. For a more complete explanation in an economics context, see Emilio Calvano and others, 'Artificial Intelligence, Algorithmic Pricing, and Collusion' (2020) 110 American Economic Review 3267.

136 Emilio Calvano and others, 'Algorithmic Collusion with Imperfect Monitoring' (2021) 79 International Journal of Industrial Organisation; Timo Klein, 'Autonomous Algorithmic Collusion: Q-Learning Under Sequential Pricing' (2021) 52 RADN Journal of Economics 538.

Earlier simulations find that reinforcement-learning algorithms could result in high prices but do not study the strategies that generate this finding, leaving open the question of whether algorithms actually learned strategies that generate high prices as an equilibrium.[137] Hansen, Misra, and Pai show in a multi-armed bandit framework with competing algorithms that pricing algorithms can also learn to set supra-competitive prices when rivals' prices are not observed.[138] They argue that these algorithms run concurrent experiments that result in overestimated own-price elasticities and, therefore, higher prices.

Abada and Lambin train Q-learning algorithms in the particular context of electricity markets, or more precisely battery charging, in a setup modeled on Tesla's "autobidder" platform.[139] They show numerically that supra-competitive prices arise not due to collusive strategies but due to a failure to fully learn competitive strategies. They discuss policy remedies and challenges for regulators that are specific to their application. While enforcing local learning (at the level of the user rather than at the level of the aggregator) works well in a simulation, it is doubtful whether it is cost-efficient in a real setting. Letting a regulated market participant intervene does not improve welfare in the simulation.

The key question explored by the simulation literature is whether algorithms that set supra-competitive prices learn to collude or fail to learn to compete. Calvano and others emphasise that algorithms can only be said to collude if high prices are underpinned by retaliatory strategies following a deviation from collusion.[140] Merely observing high prices is insufficient, as this could also indicate algorithms are not learning to compete or optimising for the wrong problem. For example, if algorithms neglect competitor reactions, they might systematically underestimate own-price elasticities and, therefore, consistently set prices higher than the competitive level.

One criticism of the simulation literature questions whether collusive strategies that arise in training environments transfer to testing environments or real markets.[141] Differences in context may make it challenging to train algorithms that collude robustly unless firms coordinate on algorithm design. With this, they refer to how the pricing algorithms are trained, particularly restricting the information their algorithms can operate on to avoid overfitting to rivals' strategies. However, as Calzolari and Hanspach document, some firms offering sales algorithms rely on training in real-life environments, so it is unclear whether there is any comfort in the idea that too simplistic, artificial training environments might hamper algorithmic collusion.[142] In addition, reinforcement learning algorithms might be costly, particularly if the state-space is high-dimensional, as it increases the number of training cases exponentially.

Overall, the simulation literature confirms that pricing algorithms can learn collusive strategies that result in supra-competitive prices in controlled setups. Simple yet effective strategies of reward and punishment that underlie these strategies can occur as emergent properties in multi-agent learning. These strategies are familiar to economists from the classic literature on tacit collusion. However, further testing is needed on how these algorithms perform in real-life environments. It is not a-priori clear when the added complexity of an actual marketplace with sophisticated firms effectively limits algorithmic collusion.

137 Ludo Waltman and Uzay Kaymak, 'Q-Learning Agents in a Cournot Oligopoly Model' (2008) 32 Journal of Economic Dynamics and Control 3725.

138 Karsten Hansen, Misra Kanishka and Mallesh Pai, 'Frontiers: Algorithmic Collusion: Supra-Competitive Prices via Independent Algorithms' (2021) 40 Marketing Science 1.

139 Ibrahim Abada and Xavier Lambin, 'Artificial Intelligence: Can Seemingly Collusive Outcome Be Avoided?' (2023) Management Science.

140 See fn 134.

141 Nicholas Eschenbaum, Filip Mellgren and Philipp Zahn, 'Robust Algorithmic Collusion' (2022) arXiv.org.

142 Giacomo Calzolari and Philip Hanspach, 'Pricing Algorithms Out of the Box: A Study of the Algorithmic Repricing Industry' (2022) *working paper*.

### *C. The Experimental and Empirical Literature*

Lab experiments have been used to address the issue of human-machine interaction. They are an established tool to understand human learning. Human test subjects have been found to quickly converge on the theoretically predicted Nash equilibria in a plethora of circumstances, including collusion. Dal Bó and Fréchette point out the sharp conditions under which cooperation arises in infinitely repeated games.[143] Normann and Sternberg let algorithms and human experiment participants compete and find that “firms employing an algorithm earn significantly less profit than their rivals”.[144] (Un)certainty about the actual presence of an algorithm does not significantly affect collusion, although humans seem to perceive algorithms as more disruptive. This is consistent with some empirical literature results that emphasise the importance of several, if not all, firms in a market adopting an algorithm to obtain higher prices. In the field of human-machine interaction, phenomena such as algorithm aversion appear, which have also been of interest to the psychology literature.[145] Thus, the ability of repricing algorithms to set high prices is moderated by consumers’ perceptions and expectations of prices.

A major reason to study pricing algorithms empirically is the uncertainty about their effect on prices. A limited number of empirical studies have been conducted to analyse the effect of pricing algorithms on retail prices in different industries and locations. Table 1 summarises some current papers that include substantial empirical analysis of pricing algorithms, reporting the industry, time period, data source, location and key results.

**Table 1: Overview of empirical papers studying pricing algorithms**

| Authors | Industry | Time period | Data source | Key results |
|---|---|---|---|---|
| Chen, Mislove and Wilson (2016) | Online retail | 2014 - 2015 | Scraped public data | Buy box non-price determinants, identification of dynamic pricing |
| Assad and others (2021A) | Gasoline | 2016 - 2019 | Public data set | Increased prices in duopolies, wide algorithm adoption matters, market structure matters |
| Brown and MacKay (2021) | Over-the-counter medicine | 2018 - 2019 | Scraped public data | Data-driven model explains high and dispersed prices, greater effect of mergers on prices |
| Hortaçsu and others (2022)[146] | Airlines | 2019 | Proprietary data | Organisations constrain pricing |
| Aparicio, Metzman and Rigobon (2021) | Online grocery retail | 2006 - 2017 | Scraped public data | Greater online price dispersion for multichannel retailers |
| Musolff (2022) | Online retail | 2018 - 2020 | Proprietary data | Algorithms facilitate tacit collusion |
| Holt, Igami and Scheidegger (2022)[147] | Gasoline | 2001 - 2020 | Public data | Screening methods for price cycles, impact proper screens for collusion |

143 Pedro Dal Bó and Guillame Fréchette, ‘The Evolution of Cooperation in Infinitely Repeated Games: Experimental Evidence’ (2011) 101 American Economic Review 411.

144 Hans-Theo Normann and Martin Sternberg, ‘Human-Algorithm Interaction: Algorithmic Pricing in Hybrid Laboratory Markets’ (2023) 152 European Economic Review.

145 Berkeley Dietvorst, Joseph Simmons and Cade Massey, ‘Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err’ (2015) 144 Journal of Experimental Psychology 1.

146 Ali Hortacsu and others, “Organizational Structure and Pricing: Evidence from a Large U.S. Airline” (2022) Cowles Foundation Discussion Paper no. 2312R.

147 Timothy Holt, Mitsuru Igami and Simon Scheidegger, ‘Detecting Edgeworth Cycles’ (2022) arXiv:2111.03434.

Chen, Mislove and Wilson study sellers in scraped pricing data from the Amazon marketplace.[148] They propose methods to identify algorithmic sellers and find that these sellers typically win the Buy Box and match closely the lowest price (but not the Amazon price due to additional charges that third-party sellers face). Brown and MacKay collect data on pricing by online pharmacies and retailers selling over-the-counter medicine.[149] They document stylised facts about repricing speed, mainly that some sellers change prices faster than others and that these firms generally charge lower prices and react faster to competitor price changes. The authors use their findings to motivate a theoretical model of asymmetric pricing speeds. Assad and others study the German gasoline industry, taking advantage of publicly available data sets a public authority provides.[150] They find that the gas stations that adopt pricing algorithms increase margins in non-monopoly markets (based on ZIP codes as geographic markets). They find no significant effect of adoption on margins in monopoly markets. Margins in duopoly markets increase only when both competitors adopt algorithms. The authors consider their findings generally consistent with tacit collusion. Musolff studies pricing cycles on the Amazon marketplace using proprietary data.[151]

1. We summarize the most important questions tackled in this literature as follows:
2. How commonly do sellers use pricing algorithms?
3. What is the effect of pricing algorithms on pricing patterns?
4. What is the effect of pricing algorithms on average prices?
5. How does competition affect the impact of pricing algorithms?

Question 4 might stand out because it differs from how the question is often phrased. Researchers commonly ask “what is the effect of algorithms/AI/machine learning on competition?”. However, a critical finding of the literature is that the adoption of pricing algorithms yields differential impacts depending on the market structure. By contrast, little research has been done to identify an effect of the adoption of pricing algorithms on market structure (in particular, entry and exit).

Varian shows that much that is discussed regarding algorithmic collusion is very similar indeed to the older literature on equilibria in repeated games.[152] The question of algorithmic collusion can be boiled down to whether pricing algorithms converge to collusive equilibria in repeated games. All markets that have been studied so far have existed before the introduction of pricing algorithms. Therefore, the question at stake is really whether adding pricing algorithms to the environment has led to coordination to different (in particular higher-price) equilibria.

Although much attention has been on the ability of algorithms to collude, pricing algorithms may impact average prices through channels other than collusion, such as alleviating human biases and systematic errors in pricing (or introducing systematic prices of their own) or drawing on more and alternative data relative to traditional pricing, which may result in higher or lower average prices, depending on circumstances. If we follow the literature in assuming that algorithms are somehow superior to humans in choosing profit-maximising prices, the impact of algorithms depends on the pricing bias of the human decision-maker.

148 Chen, L., Mislove, A., & Wilson, C. (2016). ‘An empirical analysis of algorithmic pricing on amazon marketplace.’ In *Proceedings of the 25th international conference on World Wide Web.*

149 Zach Brown and Alexander MacKay, ‘Competition in Pricing Algorithms’ (2023) American Economic Journal.

150 Stephanie Assad and others, ‘Algorithmic Pricing and Competition: Empirical Evidence from the German Retail Gasoline Market’ (2021B) CESifo Working Paper 8521.

151 Leon Musolff, ‘Algorithmic Pricing Facilitates Tacit Collusion’ (2022) Proceedings of the 23rd ACM Conference on Economics and Computation, 32-33.

152 Hal Varian, ‘Artificial Intelligence, Economics and Industrial Organisation’ in Ajay Agrawal, Joshua Gans and Avi Goldfarb (eds), *The Economics of Artificial Intelligence (University of Chicago Press 2019).*

Algorithms then merely choose the profit-maximising price. If humans initially set these prices excessively high, introducing pricing algorithms can lead to lower prices. Clearly, by the same mechanism, algorithms could as well result in an upward price adjustment, if the human bias meant lower-than-monopoly prices in the first place. Hortaçsu and others (2022) describe how coordination within organisations can result in an additional constraint on the use of repricing algorithms.

It is also important to acknowledge the limitation of analysing average prices, which most regression analyses default to. Suppose prices are, for example, higher on average after the adoption of pricing algorithms but also exhibit higher variance. In that case, forward-looking consumers might purchase more often during periods of lower prices.[153] So, higher average prices are not proof of consumer harm if algorithmic pricing at the same time allows consumers to make a bargain at certain times.[154] Therefore, documenting pricing patterns together with average prices is essential to understanding potential consumer harm. In other words, looking at pricing algorithms from just the seller side misses the overall picture of their impact on transaction prices. If, for example, following the introduction of pricing algorithms prices increase and stabilise, it is more likely to conclude that there is harm for consumers than if prices remain variable.[155]

As mentioned in the previous section, the identification of algorithmic sellers is a problem that is common to all empirical papers in this field. To our knowledge, no published paper uses a data set of competing sellers that includes both transaction prices and the observed (rather than inferred) use of pricing algorithms. All papers mentioned in this section infer algorithm usage from some observable characteristic of seller behaviour.

Most of these approaches follow Chen, Mislove, and Wilson, who define two main criteria to infer that a seller uses pricing algorithms:[156] The first criterion is a close correlation of a seller's price series against a meaningful benchmark, such as the lowest- or second-lowest price. The second criterion is a high frequency of price changes. The cut-off values for both criteria were chosen empirically, that is, eyeballed from the “kink” or “knee” in the empirical distribution of these frequencies. This is in line with Aparicio, Metzman and Rigobon, who find that pricing algorithms of US online grocery retailers update prices very frequently in tiny magnitudes and often match competitors' prices.[157]

Assad and others deal with the adoption of algorithms by retail gasoline stations similarly, focusing on structural breaks in observable features of the price series.[158] These features are (i) number of price changes, (ii) average size of price changes, and (iii) rival response time. They also introduce the notion of brand adoption. In a setting where individual retail outlets belong to a larger chain making strategic decisions, a brand-level decision to adopt pricing algorithms (or to encourage outlet owners or franchisees to do so) can impact adoption. They find brand size to be the only significant determinant of the brand decision to adopt pricing algorithms during their sample period. They use brand adoption as an instrument to deal with endogeneity in station-level adoption of pricing algorithms. Other studies do not make inferences about which sellers might use algorithms but simply describe general trends in the observed pricing of online retailers, which they then argue are consistent with the use of pricing algorithms.[159]

153 Alessandro Acquisti and Hal Varian, ‘Conditioning prices on Purchase History’ (2005) 24 Marketing Science 367.

154 Consumers that search for flights on price comparison engines sometimes face price ranges that inform them of average prices and the range of prices on their desired route, for example when using Google Flights. Websites such as Keepa (https://keepa.com) or CamelCamelCamel track prices on Amazon and can send automated alerts to consumers. Importantly, both of these services offer simple and intuitive alerts that do not require any technical expertise.

155 Martin Huber and David Imhof, ‘Machine Learning With Screens for Detecting Bid-Rigging Cartels’ (2019) 65 International Journal of Industrial Organization 277.

156 Le Chen, Alan Mislove and Christo Wilson, ‘An Empirical Analysis of Algorithmic Pricing on Amazon Marketplace’ (2016) Proceedings of the 25th International Conference on the World Wide Web, pp. 1339–1349.

157 Diego Aparicio, Zachary Metzman and Roberto Rigobon, ‘The Pricing Strategies of Online Grocery Retailers’ (2021) NBER WP 28639, 26.

158 Assad and others (2021B).

159 Brown and MacKay (2023).

## 5. Conclusion

Thanks to machine learning, algorithms are superseding the human decision-maker in setting prices, and, as such, they are in the limelight of competition policy. The code, training data and the market context of operation all affect the behaviour of repricing algorithms. Their ambivalent impact on competition calls for a case-by-case analysis rather than broad brush per se prohibitions. On the positive side, repricing algorithms are a powerful tool to extract value from Big Data that can foster market transparency and efficiencies and spur consumer welfare. Nonetheless, the same beneficial properties of algorithmic pricing can turn into negative consequences, such as algorithmic collusion, that might be tackled under Art. 101(1) TFEU. Usual competition law categories of anti-competitive agreements and concerted practices can apply where repricing algorithms execute a pre-existing anti-competitive agreement (the Messenger scenario), facilitate the formation of a cartel (the Hub and Spoke) or disguise sensitive information exchanges (the Predictable Agent). Instead, Art. 101(1) TFEU falls short of autonomous collusion by repricing algorithms without human intervention or actual information sharing (the Digital Eye). Absent market dominance, EU law does not prevent parallel behaviour resulting from the unilateral and rational adaptation of each firm's conduct on the market.

Despite the limitation of Art. 101(1) TFEU vis-à-vis autonomous algorithmic collusion, the technical literature on algorithmic pricing moderates the competition policy fears. Algorithmic pricing does not always lead to coordinated higher prices. Early speculation that warned of ubiquitous algorithmic collusion has not been confirmed. However, the empirical literature has accepted that the adoption of pricing algorithms leads to changes in pricing behaviour, in particular frequent price changes and, in some markets, recurring price cycles.

In controlled environments, simple algorithms are capable of learning complex reward-and-punishment strategies. In theory, these strategies are capable of supporting collusive behaviour. Empirically, higher prices seem to be a more likely outcome in more concentrated markets and with universal adoption of pricing algorithms. However, even higher average prices do not necessarily imply harm to consumers if prices also cycle. Forward-looking consumers may still be able to purchase at equal or even lower prices compared to a situation without algorithmic pricing. If pricing algorithms learn market features with a high degree of precision, the resulting pricing patterns may also be explained as a form of (potentially efficiency-enhancing) price discrimination rather than algorithmic collusion.

Therefore, despite the ability of algorithms to draw on superior data and outperform human decision-makers, there is no basis to assume that consumers lose out when pricing is algorithmic. There are open questions before we can accurately describe the effect of pricing algorithms on prices and market structure. Finally, future research should clarify the effect of algorithmic pricing on consumers, accounting for the strategic reactions of buyers to this new phenomenon.

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