Antitrust Law and Coordination Through AI-Based Pricing Technologies

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Abstract Price is the core element of commercial transactions and an important parameter of competition. One of antitrust law's aims is to ensure that market prices form under the laws of supply and demand, and not after the whims of monopolists or cartelists. Innovations in computer and data science have brought about pricing technologies that rely on advanced analytics or machine learning (ML) techniques, which could strengthen existing bargaining power disparities in part by supporting price coordination among competitors.

Existing research establishes a theoretical framework for competitive harm through coordination, showing that pricing technologies can lead to near-cartel price levels while avoiding anti-cartel prohibitions. This contribution builds on that framework, taking into account up to date empirical, game-theoretic, and computer science literature on pricing technologies to produce a taxonomy of those technologies. We then employ a comparative approach to identify the legal effects of various pricing technologies at a more granular level under EU and US antitrust law. The contribution supports greater understanding between economists and policy-makers regarding the analysis and treatment of AI-based pricing technologies.

1 Introduction

Price is the core element of commercial transactions and an important parameter of competition. One of antitrust law's aims is to ensure that market prices form under free competition, so that the laws of supply and demand operate to maximize consumer welfare. One instance where prices do not result from competition is when

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there is anti-competitive coordination in a market. Anti-competitive coordination is prohibited under various provisions of antitrust law, most importantly under cartel prohibitions (e.g. Section 1 of the Sherman Act in the US and Article 101 of the Treaty on the Functioning of the European Union) and under merger rules (where mergers producing coordinated effects should be prohibited).

The prevailing opinion in antitrust scholarship and enforcement practice has been that, unless there is explicit coordination between competitors, coordination is unlikely to occur in markets with four or more players (Stigler 1964). When coordination is not explicit but tacit, it will rarely be caught by antitrust rules. Under the current state of the law in both the US and EU, tacit coordination is by definition not caught under cartel prohibitions, since existing rules require some evidence of a meeting of the minds between cartel participants to trigger the application of the prohibition. To show that there has been a meeting of the minds, traditionally, evidence about communication between cartel participants, records of a meeting, or exchange of information through a third party is necessary. While there is reason to believe this limitation on enforcement against coordinated outcomes enables price and non-price effects that harm consumers, to date there is not a broadly accepted approach to preventing these outcomes as a matter of conduct enforcement. Increased likelihood of tacit coordination as a result of a merger could potentially be caught under merger laws, but competition enforcers have rarely prohibited mergers because of their potential coordinated effects. In the instances in which they have tried to block such mergers, they have regularly been unsuccessful due to high legal standards for proving tacit coordination imposed by courts.[1]

The conventional wisdom that anti-competitive coordination in the form of tacit collusion is unlikely to occur is being challenged by recent studies in game theory and rapid technological developments (OECD 2017). Innovations in computer and data science have brought about pricing technologies that rely on advanced analytics or machine learning (ML) techniques, which are thought to be capable of self-learning and sustaining price coordination among competitors. It is uncertain whether antitrust laws would catch such algorithmic price coordination. It would depend on (a) the capabilities of the technology used and their potential for causing competitive harm, and (b) on the interpretation of antitrust law. This chapter aims at bringing more clarity to these two dimensions to contribute to ongoing debates on antitrust law and AI-based pricing technologies.

We start by laying out the state of the art on pricing technology and algorithmic tacit collusion in law, microeconomics and computer science literature. Next, we engage with a variety of AI-based technologies that can be deployed for dynamic pricing. We then assess various technological options from an EU and US antitrust perspective before outlining policy approaches and a future outlook.[2]

[1] In the EU, an example is Case Case T-342/99 *Airtours,* where the General Court held that the Commission had not been able to show coordinated effects from a merger that would lead to a blocking of the merger.

[2] The Chapter takes into consideration policy developments until 17 February 2023.

2 Algorithmic Pricing and Collusion

Pricing is a core part of companies' competitive strategy. In settings where prices can be adjusted easily and frequently, as for example in the case of online retail or stationary retail with electronic price tags, companies can optimize their pricing by using dynamic pricing techniques (Den Boer 2013). Dynamic pricing allows companies to rapidly react to changes in demand or inventory levels, and to respond to competitors' behavior and market trends.

Increasingly available amounts of data together with algorithms can support and enhance dynamic pricing. Simple algorithms can implement pre-existing "analogue" pricing rules, such as matching the lowest competitor price. In this case, the use of algorithms allows for the automation of price setting and for faster reactions to a rival competitor's price change (CMA 2018). Alternatively, more sophisticated machine learning algorithms can autonomously choose which data to base pricing decisions on and can learn about optimal pricing strategies (CMA 2018).

The impact of pricing algorithms on market competition is ambiguous. On the one hand, they can have pro-competitive effects, like allowing managers to make faster and better decisions or directly reducing costs by fully automating decision-making (CMA 2018). In addition, they might contribute to markets clearing faster and more efficiently (CMA 2018). On the other hand, concerns have been raised that pricing algorithms might facilitate explicit, tacit, or even unintentional coordination of market behavior, leading to collusive market outcomes and consumer harm (CMA 2018).

Academic literature in antitrust law and policy is split regarding the risks for competition from firms' algorithmic pricing. Some authors suggest that markets are being fundamentally transformed by the use of algorithms, and that the risk of widespread algorithmic collusion is real (Ezrachi and Stucke 2016; Mehra 2016). Ezrachi and Stucke (2016) propose four scenarios in which the use of algorithms in pricing can lead to collusive outcomes. First, in situations in which algorithms are used to support an explicit price-fixing agreement by implementing the agreed conduct or detecting any deviations from it. An example of this is the Amazon poster-sellers' cartel which was prosecuted in the US and the UK.[3] In this case, competitors on Amazon reached an express agreement as to the features of the algorithm to be employed in establishing prices on Amazon, with the effect of price coordination that would not have happened in the absence of the agreement. As the UK Competition and Markets Authority described it, an initial verbal price fixing agreement was later implemented using pricing software. This was contrary to antitrust law. Second, in hub-and-spoke situations in which many market actors delegate their pricing decisions to the same algorithm from a third-party developer, Ezrachi and Stucke (2016) argue that there is a risk of price alignment steered by

[3] United States v. David Topkins, Plea Agreement, Crim. No. 15-201 (N.D. Cal. Apr. 30, 2015); Online sales of posters and frames, Case No. 50223 (CMA 12 Aug. 2016).

the hub. Third, in situations where companies unilaterally deploy simple algorithms with predictable actions, e.g. algorithms implementing 'win-continue lose-reverse' rules or algorithms that match competitor prices, price alignment can occur. Last, when advanced machine learning algorithms are designed by companies to achieve a goal, like profit maximization, and are left to themselves to figure out the optimal pricing strategy (autonomous agent schemes), they autonomously could learn to collude. In particular, in the case of autonomous agent schemes, this strand of the literature maintains that current antitrust laws are ill-suited for sanctioning this type of conduct.

The opposite view maintains that the claims about risks from algorithmic pricing in debates on AI and antitrust law are "science fiction" (Petit 2017; Schwalbe 2019). This strand of the literature considers in particular autonomous algorithmic collusion as something that is far removed from present day capabilities of the technology and point to the fact that no empirical evidence of autonomous collusion has been presented so far (Schwalbe 2019; Gautier et al. 2020). In addition, this strand of the literature maintains that the currently possible forms of algorithmic collusion do not pose any fundamental challenges to existing antitrust rules (Gautier et al. 2020). Some critiques might be questioned as continuous technological improvements increase the possibility of theorized outcomes. Furthermore, the line between human-assisted and autonomous algorithmic collusion may not always be easy to draw, thus leaving more grey areas for the treatment of algorithmic collusion under current antitrust law than critics maintain.

Literature in microeconomics echoes this split. For economists, collusion is defined as a situation when firms use strategies implementing a "reward-punishment scheme designed to provide incentives for firms to consistently price above the competitive level" (Harrington 2018). The question as to whether algorithms can learn to engage in collusion and to "punish" deviations from collusive behavior has been discussed both theoretically, empirically, and in simulations. For collusion to occur in markets without algorithms, certain structural conditions can facilitate collusion, such as when there is profit to make from colluding, there are few competitors, players on the market are symmetric, entry barriers are high, there are repeated interactions of market players, there is seller-side homogeneity, and there is a high level of transparency that allows competitors to observe each other's behavior (Stigler 1964; Green et al. 2013). These same structural conditions also support non-collusive coordination, sometimes called tacit collusion, oligopolistic coordination, or interdependent conduct, which has not been treated as violating either US law (Section 1 of the Sherman Act) or EU law (Article 101 TFEU).[4]

An early analysis of this problem is offered by Donald Turner, who concluded that tacit coordination should not be treated as an agreement because it merely reflects the behavior of a rational oligopolist, acting in its independent best interest (Turner 1962, pp. 665–666). In particular, there is no conduct that can be condemned by way of remedying the outcome, short of an injunction operating as a price control

[4] *See infra*.

(Kaysen and Turner 1959, pp. 110–119, 266–272).[5] Importantly, Turner identifies as not affected by his conclusion conduct "designed to convert an imperfect oligopoly pricing pattern into a perfect one by eliminating uncertainties" (Kaysen and Turner 1959, pp. 670–673). Richard Posner later advocated for an alternative approach to the problem in which oligopolists "base their pricing decisions in part on anticipated reactions to them" with the resulting "tendency to avoid vigorous price competition" (Posner 1969, p. 1564). Posner took issue with Turner's suggestion that an oligopolist might merely find itself in a market where the profit maximizing activity was to consider its competitor's responses, leading to coordinated outcomes. Instead, Posner identifies a number of features required for successful oligopolistic coordination, including substantial similarity of product and reliable knowledge of other firm prices; because those and other features come about by voluntary action, it is possible to remedy the oligopoly pricing by forbidding those actions (Posner 1969, pp. 1575–1576).

The deployment of pricing algorithms is thought to be able to bring about or to magnify some of the conditions that lead to coordinated outcomes, including: market concentration, speed, efficiency, transparency, and stability. Gal (2019), for example, argues that algorithms' speed allows these algorithms to detect and punish deviations from charging supra-competitive prices faster than humans, thus making collusion more stable. Pricing algorithms also process much higher amounts of data than humans, thus making them more efficient in pursuing a collusive strategy. In addition, the argument has been made that due to algorithms' strategy being "encoded", it would be easier for algorithms to "read" other algorithms' strategies thereby increasing market transparency (Gal 2019). In addition, algorithms' prediction capacity based on past market data might increase transparency in terms of more accurately predicting future demand (Miklós-Thal and Tucker 2019). Lastly, if companies need to rely on pricing algorithms in order to be able to get a competitive advantage on markets, this might raise market concentration, as the development or purchase of sophisticated pricing algorithms is costly and only incumbents and larger players will have the resources to compete (Chen et al. 2016; Dorner 2021).

While there is considerable evidence on firms using pricing algorithms (Chen et al. 2016; European Commission 2017), there is scant evidence showing a causal relationship between pricing algorithms and collusive outcomes. One recent study from the German gasoline market, however, showed that after gas stations adopted algorithmic pricing technology, gradual price rises lead to permanent price increases indicating a decrease in competition (Assad et al. 2020). In this study, the authors show that in the aftermath of algorithmic pricing software becoming available and widely adopted by German gas stations, profit margins in non-monopoly markets

[5] Turner does not argue that nothing should be done, instead advocating a structuralist approach of curbing market power by legislation.

and in duopoly markets where both stations adopted algorithmic pricing increased considerably.[6]

Due to the difficulty of finding real-world evidence of tacit algorithmic collusion, with the German gasoline market study being the first and only of its kind to date, several studies have tested learning algorithms' capacity to collude in simulations of repeated games. Calvano et al. (2019, 2020) provided a first experimental study where they could show that two Q-learning[7] algorithms could autonomously learn to collude by implementing a reward-punishment scheme in the framework of a repeated Bertrand oligopoly setting.[8] The results showed that, after several iterations, the equilibrium strategy of the algorithms in the repeated game led to sustained supra-competitive price levels. Klein (2021) provides further evidence on the capacity of Q-learning algorithms to learn how to collude in situations of sequential pricing.

The relevance of these studies for policy, however, has been questioned due to the very slow learning process of Q-learning algorithms, which make their use by businesses unrealistic (Ittoo and Petit 2017; Gautier et al. 2020; Dorner 2021). The studies have also been criticized for being difficult to extend to settings more than two-agents due to problems in scalability and learning in a non-stationary environment where several competitors are adjusting their behavior constantly. Lastly, the studies' inapplicability to scenarios with non-homogeneous goods has been criticized (Ittoo and Petit 2017; Gautier et al. 2020). In other words, the simulations that show the possibility of Q-learning algorithms learning to collude have been criticized for being too far removed from the conditions under which real markets work, thus questioning the policy implications from their findings. Nonetheless, the studies show theoretically that two algorithms that are unilaterally deployed and that are not designed to communicate can eventually learn to tacitly collude and produce coordinated outcomes. In addition, the Swedish Competition Authority recently published a report corroborating the evidence from prior experiments and showed the possibility of collusive outcomes also when a variety of learning algorithms were mixed (Q-learning, SARSA, and PG), and when Q-learning agents were programmed asymmetrically (Konkurrensverket 2021).

It is unclear in how far the findings from simulations with Q-learning algorithms apply to other machine learning techniques (Gautier et al. 2020). Hettich (2021) provides initial evidence for deep Q-learning algorithms (DQN)[9] learning how to collude significantly faster than simple Q-learning algorithms. According to his study, collusion disappears in simulations with more than 7 firms. Furthermore, collusion is not hindered when the other algorithms are simple, rule-based algorithms,

[6] The geographic markets for gasoline stations are local, each potentially having a different number of players. The authors drew 1 km radii around gas stations to define the relevant market. This is why there are many separate relevant retail gasoline markets within the territory of Germany in this study that allow for comparisons across them.

[7] We elaborate on Q-learning in the next section.

[8] The Bertrand model of competition describes interactions among firms that set prices, the quantity sold being determined by the choices of their customers based on the set price.

[9] DQN algorithms combine a Q-learning algorithm with a Deep Neural Network.

but is hindered if there are various learning algorithms with different characteristics (e.g. differences in learning pace). More research is needed to understand and measure the risks of collusion stemming from DQNs used in pricing.

In computer science, there is an important literature on the capacity of reinforcement learning algorithms to cooperate in repeated prisoner's dilemma (Schwalbe 2019 for an overview), which is comparable to the setting of two firms in a Bertrand oligopoly. The literature has explored the focus on the connection between learning, communication, and cooperation. In two recent studies modelling prisoner's dilemma situations, two important factors for learning cooperation by self-learning algorithms were identified. First, cooperation is easier to achieve when lower degrees of coordination were needed to achieve the highest reward (Leibo et al. 2017). Second, that cooperation was much more easily achieved if algorithms could send signals to each other through a communication protocol (Crandall et al. 2018). Applying these insights to pricing algorithms, this literature would suggest that collusion is more likely the less complex the algorithms and the environment they operate in are (Schwalbe 2019). In addition, as in the case of human agents, communication between algorithms will increase the likelihood of collusion.

All in all, the uncertainty as to whether pricing algorithms can collude and what level of harm they can cause when they align prices on markets persists. Nonetheless, this uncertainty will likely not have vanished before a competition authority or court might have to deal with a case giving rise to questions surrounding the legality of pricing algorithms that are not a simple tool to implement a cartel as in the Amazon Poster cases discussed above. Furthermore, the literature has already hinted to features in the design of pricing algorithms that, at least in theory, should make algorithmic collusion more or less likely. In the next section we discuss various possible AI-based pricing technologies and their characteristics. Subsequently, we give a possible outline for how to deal with different characteristics of pricing algorithms under antitrust rules.

3 Varieties of AI-Based Pricing Technologies

Dynamic pricing can be implemented with the help of a broad range of algorithms. There are very simple if-then algorithms, or rule-based agents, without any learning capacities. Such algorithms can, for example, implement simple business rules in a non-transient manner, i.e. they will not change their behavior by learning from past interaction. There are third-party developers offering these kinds of simple pricing solutions on the market, and they appear to be the most common form deployed today (CMA 2018).

More sophisticated algorithms that are capable of learning, can be categorized as a form of AI. Artificial Intelligence (AI) can take many forms. The recently proposed EU AI Act[10] defines artificial intelligence systems as "software that is developed with one or more of the techniques and approaches listed in Annex I and can, for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations, or decisions influencing the environments they interact with". Annex I contains three examples of AI systems, the most important for us being machine learning approaches.[11]

Machine learning covers a variety of computer programs that learn from experience (Russell and Norvig 1995). The main fields within machine learning are supervised learning, unsupervised learning, and reinforcement learning. Supervised learning entails teaching an algorithm with example input-output pairs a mapping function that will allow the algorithm eventually to predict outcomes for new input data autonomously. Supervised and semi-supervised learning are applied in many fields where training occurs with labeled data, e.g. in the case of algorithmic content moderation on social media. Supervised learning is also used for regressions, and, when deployed in pricing, can thus enable pricing algorithms to predict future trends.

Unsupervised learning, on the other hand, entails giving an algorithm only input data without output variables. The learning task of the algorithm is then to figure out patterns in the input data. Applications of unsupervised learning include pattern recognition in big data and recommender systems. Unsupervised learning can help in pricing decisions in order to discover new correlations or to gain insights across product or geographic markets. It might, for example, allow a cosmetics seller to have new insights about how a seemingly unrelated event, e.g. the weather, impacts demand for cosmetics.

Lastly, reinforcement learning is the machine learning technique that has been deployed in the repeated game simulations discussed in the previous section. Reinforcement learning trains algorithms to make a series of decisions in a complex environment in order to achieve a certain objective through trial and error. Q-learning is one form of reinforcement learning.[12] It enables agent to implement a reward-maximizing strategy in an unknown environment over time. The agent learns by choosing and performing an action in a certain state, estimating the reward for taking that action, and updating its function based on the positive or negative reward

[10] Proposal for a Regulation Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act) and Amending Certain Union Legislative Acts, of 21 April 2021, COM(2021) 206 final.

[11] The other two examples are logic- and knowledge-based approaches on the one hand, and statistical approaches, Bayesian estimation, search and optimization methods on the other. This definition, however, is not final yet, and has been criticized by various actors in the policy process, including the EU Council (see https://www.euractiv.com/section/digital/news/eu-council-presidency-pitches-significant-changes-to-ai-act-proposal/).

[12] Other types of reinforcement learning are SARSA and policy gradient (PG) methods, the Swedish Competition Authority provides a comparison between Q-learning, SARSA and PG in its November 2021 Report (Konkurrensverket 2021, pp. 17–19).

received.[13] This process is then repeated over and over until the learning process is stopped. In the simulations by Calvano et al. (2019, 2020) and Klein (2021) this process allowed the algorithms to learn to collude over time.

A different structural form of learning relies on so-called deep neural networks (DNN). DNN were inspired by the neuronal structure of the human brain, and consist of multiple interconnected layers of artificial neurons. In DNN, learning can again be supervised, unsupervised, or reinforced (Nicholson 2021). DNNs can learn differently and faster, by modifying connections between artificial neuros and due to each layer being able to execute a different task. DNN is the underlying AI technology for automatic speech recognition, image recognition, and natural language processing, and can also be deployed for predicting and optimizing pricing. It is sometimes referred to as a "black box" because the processes that yield an output are difficult or impossible to understand.

An alternative to DNN are Random Forests that combine the predictions of many decision trees (Montantes 2020). In comparison to DNN, they require less data and are computationally more efficient. They also tend to be more transparent in comparison to a DNN because they allow to make connections between the variables and the prediction model they generate.

The literature has shown that various characteristics of machine learning algorithms can influence the capacity to cooperate/collude. These include memory of prior interactions, the learning pace, the complexity of algorithms (the more complex, the less likely to collude because behavior is difficult to "read" for other algorithms) (Schwalbe 2019; Hettich 2021), and their capacity to communicate (Schwalbe 2019).

4 Algorithmic Collusion in US Antitrust Law

4.1 The Necessity of "Agreement"

The core requirement for a violation of Section 1 of the Sherman Act is the existence of an agreement among two or more independent economic actors.[14] The agreement requirement is also present in some cases under Section 2, which outlaws "combin[ing] or conspir[ing] to monopolize."[15] (Because there is no meaningful difference between the Section 2 conspiracy and the Section 1 conspiracy, the analysis here does not treat them separately.) The question of agreement is binary:

[13] More detailed and technical descriptions of how Q-learning works can be found e.g. in Ittoo and Petit (2017).

[14] United States Code, Title 15, Section 1 ("Every contract, combination in the form of trust or otherwise, or conspiracy, in restraint of trade or commerce among the several States, or with foreign nations, is declared to be illegal . . . ."

[15] *Id.* Section 2.

conduct occurring by agreement must be analyzed for its legality under either the rule of reason or *per se* analytical approaches, but conduct not occurring by agreement is immune from challenge under Section 1, irrespective of the likelihood of consumer harm.

4.2 Non-Agreement Coordination

Most important for the analysis here is the broad category of non-agreement coordination that fits under the labels "tacit collusion," "tacit coordination," "interdependent conduct," "conscious parallelism," and "oligopolistic coordination." This analysis employs the label "non-agreement coordination", best understood as the outcome that occurs when competitors all recognize their independent best interest is achieved not by full-throated competition but by coordination with competitors. An example, frequently cited, is that of competing gas station proprietors who price in parallel fashion despite a lack of implicit or explicit agreement between them (Huffman 2008, p. 646). The US Supreme Court has repeatedly recognized this reality, in cases including *Bell Atlantic Corp v. Twombly* (2007),[16] and held that coordination among economic actors that is caused by their pursuing their independent best interest does not constitute an agreement (Huffman 2008, at 648–649). Two primary reasons support the approach of treating non-agreement coordination as outside of the prohibitions of Section 1. First is a simple and formalistic matter of statutory interpretation: Section 1 does not outlaw conduct by firms pursuing their independent best interest.

Second is the problem of remedying non-agreement coordination. To prohibit oligopoly conduct, courts or regulators would be required to order economic actors not to pursue their independent best interest, by—for example—not taking into account the effect on competitors (and their likely response) to pricing decisions. A rule against oligopoly pricing would effectively be a requirement of naïve or irrational pricing conduct (Turner 1962, p. 692; Whinston 2006, p. 52).

US law has developed in a series of cases to exempt non-agreement coordination entirely from the reach of the Sherman Act. Hylton (2018) argues that Judge Posner's 2015 opinion in *In re Text Messaging Antitrust Litigation* represents the most definitive statement of this principle—as one remarkable example from that opinion: "[T]he Sherman Act imposes no duty on firms to compete vigorously, or for that matter at all, in price."[17] Notably, *Text Messaging* suggests a complete about-face from Posner's (1969) view that the law might take steps to challenge tacit collusion (Hylton 2018, p. 5).

Courts have developed a system of requiring additional evidence, beyond observed parallel conduct, to differentiate agreement from non-agreement coordination. This "plus-factor" framework is fundamentally an evidentiary or pleading

[16] 550 U.S. 544, 553–554 (2007).

[17] *In re Text Messaging Antitrust Litig.*, 782 F.3d 867, 874 (7th Cir. 2015).

burden, meant to indicate conduct subject to liability as distinct from innocent conduct, rather than a substantive rule of law. As outlined by Kovacic et al. (2011, pp. 405–406) a plus factor is an evidentiary fact that reduces the likelihood of a non-agreement explanation for coordinated conduct. In their presence, evidence may be sufficient for circumstantial proof of agreement, which can be remedied by prohibition and sanction. In the absence of plus factors, however, there is no basis to assume actual agreement from an observation of coordination among competitors, leaving unremediable non-agreement coordination as the legally necessary conclusion.

4.3 Hub-and-Spoke

Agreements can also be reached through parallel agreements reached with a third party, acting as the "hub" in a hub-and-spoke enterprise structure (Huffman and Schmidt-Kessen 2021, pp. 8–10). The analysis of a hub-and-spoke enterprise becomes interesting if it is possible to prove an agreement around the "rim", which is horizontal among the various spokes. Recent cases in US courts, including the Seventh Circuit's decision in *Toys 'R' Us* (2000) and the Second Circuit's decision in *Apple e-Books* (2015), find horizontal agreements among competitors when the individual vertical agreements with the hub are reached with an understanding of, and reliance on, competitors' comparable agreements.[18] Hub-and-spoke enterprises have characteristics in common with non-agreement coordination, because these enterprises do not rely on actual communication between the spokes. However, unlike non-agreement coordination, it is possible to remedy the hub-and-spoke through a prohibition of the various vertical agreements.

4.4 Remedying Coordinated Conduct

One approach to remedying non-agreement coordination is to attack it indirectly, through challenging agreements or other conduct that increase the likelihood of coordination. A second is to attack the coordination directly under Section 5 of the US Federal Trade Commission Act, with its prohibition of "unfair methods of competition."[19]

With regard to the prohibition of conduct that increases the likelihood of coordination, courts and enforcement agencies interpreting Section 1 prohibit

[18] United States v. Apple Inc., 791 F.3d 290 (2015) (upholding finding of liability for a horizontal agreement among publishers orchestrated by retailer Apple, acting as the hub); Toys 'R' Us Inc. v. FTC, 221 F.3d 928 (7th Cir. 2000) (affirming FTC finding of liability for hub-and-spoke conspiracy).

[19] United States Code, Title 15, Section 5.

agreements among firms to share information where those agreements increase the likelihood of oligopolistic coordination (Clark 1983, pp. 915–918).[20] Clark categories such practices as (1) public announcements of business plans, (2) data dissemination on prices and non-price matters, (3) discount deterring practices including MFN clauses, and (4) standardization of terms of trade (Clark 1983, pp. 919–951). Page (2017) summarizes judicial treatment of the sharing of information among firms as dependent on the audience and the past, present or forward-looking nature of the communications. Broad publication to the market, consumers as well as competitors, has obvious competition-enhancing features - for example, communicating petrol prices to consumers, permitting comparison shopping while driving. Communication to competitors but not to the market facilitates tacit collusion and has limited procompetitive benefits, with typical examples including communications within industry trade associations. With regard to communications' temporal character, present or past information is less likely to be harmful than is future information (Page 2017, pp. 611–612).

Market structure is also linked to concerns for non-agreement coordination, and in merger review courts and agencies broadly consider coordinated effects as a reason to challenge or enjoin a merger. The 2010 *Horizontal Merger Guidelines* identify as coordinated conduct (1) explicit agreements, (2) a common understanding not explicitly agreed to but nonetheless enforced, and (3) parallel accommodating conduct (*Guidelines*, 2010, section 7). The *Guidelines* acknowledge that coordinated conduct includes activity that is not in itself an antitrust violation. Mergers will be challenged if by increasing concentration in a market susceptible to coordination, the incidence and effect of coordination is likely to be exacerbated (*Id*., section 7.1). Susceptibility to coordination includes, among other factors, price transparency and homogeneity (*Id.,* section 7.2). Merger review stands as a significant protection against the possibility of non-agreement coordination otherwise not subject to challenge.[21] Notably, the US Horizontal Merger Guidelines, last updated in 2010, are as of this publication ripe for revision. Given the FTC's emphasis on technology markets, and the leadership of the EU in its Draft Horizontal Guidelines (*infra*), we anticipate a revision will incorporate algorithmic collusion concerns as a factor to be considered in analyzing coordinated effects. [22]

Remedying non-agreement coordination directly under the FTC Act may in theory be possible (Dibadj 2010, pp. 606–608). The FTC Act's broad prohibition targets "unfair methods of competition," rather than the somewhat more specific

[20] Concerns for anticompetitive information sharing can also be found in the *Collaboration Guidelines* (2000, at 21, 26–27).

[21] *E.g. United States v. H&R Block Inc.*, 833 F. Supp. 2d 36, 77–81 (D.D.C. 2011) (identifying market structure conducive to non-agreement coordination as a basis for enjoining merger in tax preparation software market).

[22] Federal Trade Commission and Justice Department Seek to Strengthen Enforcement Against Illegal Mergers, 18 Jan. 2022, available at https://www.ftc.gov/news-events/news/press-releases/2022/01/federal-trade-commission-justice-department-seek-strengthen-enforcement-against-illegal-mergers.

"contract, combination.. ., or conspiracy" under the Sherman Act. And the FTC lacks the power to impose draconian penalties, limiting concerns that criminal penalties or treble-damages liability will disincentivize aggressive competitive behavior (Huffman 2022a). However, the remedial concern of how to address the conduct directly—whether to order competition, or to order pricing at marginal cost, or other outcome—remains. The FTC has not challenged non-agreement coordination directly, instead targeting its prosecutions at facilitating practices that tended to lead to coordination (see Clark 1983, pp. 948–951).

5 Algorithmic Collusion in EU Antitrust Law

5.1 Coordination by Agreement

Article 101 (1) TFEU prohibits "all agreements between undertakings, decisions by associations of undertakings and concerted practices which may affect trade between Member States and which have as their object or effect the prevention, restriction or distortion of competition within the internal market". These include in particular price fixing agreements.[23] The core piece of evidence in order to prove a violation of Article 101 (1) TFEU is that there has been communication between the parties to the agreement or concerted practice that has led to a "meeting of the minds" to fix prices. Similar to the US context, mere parallel conduct cannot be prohibited under Article 101 (1) TFEU.[24]

5.2 Non-Agreement Coordination

The EU Commission has been able to prove an anti-competitive agreement without having evidence of explicit communication between the parties before.[25] The Court of Justice of the EU found in *Imperial Chemical Industries* that "parallel behaviour may not by itself be identified with a concerted practice, it may however amount to strong evidence of such a practice if it leads to conditions of competition which do not correspond to the normal conditions of the market, having regard to the nature of the products, the size and number of the undertakings, and the volume of the said market." The Court went on to say that this was especially the case "if the parallel conduct is such as to enable those concerned to attempt to stabilize prices at a level different from that to which competition would have led". The Court thus opened the

[23] Article 101 (1) (a) TFEU.

[24] See e.g. Cases C- 40 to 48, 50, 54 to 56, 111, 113 and 114-73 *Suiker Unie;* Case 172/80 *Zünchner v Bayerische Vereinsbank;* Case T-442/08 *Cisac v Commission* [2013].

[25] Case 48/96 *Imperial Chemical Industries* [1972].

door in this judgment to considering evidence beyond the communication between the parties to contextual elements of the market in question. Nonetheless, as the EU Court of Justice judgment in *Woodpulp* stressed, if there is a plausible explanation for the conduct other than collusion, there is no violation of Article 101 (1) TFEU.[26]

Furthermore, the EU Commission states in its Guidelines on Horizontal Cooperation that it will be vigilant of companies' attempt of making markets more transparent by announcing prices publicly.[27] If several companies make public announcements sequentially, for example, this can be evidence of concertation.[28]

In its new Draft Horizontal Guidelines, [29] the Commission recognizes that the use of algorithms can increase market transparency, too, and with it the risk of a collusive outcome in the market. It notes, however, that for algorithms to bring about such outcomes, further structural conditions are required, like "a high frequency of interactions, limited buyer power and the presence of homogenous products/services". [30]In addition, at least a provable indirect information exchange via an algorithmic tool between competitors would be necessary to consider it a form of coordination that could be caught under Article 101 (1) TFEU. This could be, for example, through a shared optimization algorithm that is marketed by a single IT company and that feeds on sensitive data from various competitors. [31]

5.3 Hub-and-Spoke Coordination

A third possibility to establish that there has been anti-competitive coordination contrary to Article 101 (1) TFEU is when parties that intend to fix prices do not communicate with each other, but through a third party. In this case, the third party, acting as a middleman or hub will ultimately establish a "meeting of the minds" between the spokes (OECD 2017; Huffman and Schmidt-Kessen 2021). This was the case, for example in *AC Treuhand*,[32] where a consultancy facilitated

[26] Joined Cases C-89, 104, 114, 116, 117 and 125 to 129/85 *Woodpulp*.

[27] EU Commission (2011). Guidelines on the applicability of Article 101 of the Treaty on the Functioning of the European Union to horizontal co-operation agreements, 2011/C 11/01, 63.

[28] E.g. COMP/39.850 *Container Shipping* where the EU Commission found that regular public announcement of price increase intentions through press releases and specialized trade press made several times a year by various companies was considered a concerted practice contrary to Article 101 (1) TFEU.

[29] EU Commission (2022). Approval of the content of a draft for a Communication from the Commission – Guidelines on the applicability of Article 101 of the Treaty on the Functioning of the European Union to horizontal co-operation agreements, 2022/C 164/01. The Draft Guidelines should have been adopted by 1 January 2023, but at the time of writing (February 2023), the final version had not yet been published.

[30] Ibid, 418.

[31] Ibid, 426.

[32] Case C-195/14 P *AC Treuhand.*

the exchanges of sensitive business information between its clients that lead to alignment of prices on the market.

As mentioned above, especially if several actors in a same market purchase pricing algorithms from the same third-party developer, a hub-and-spoke scenario might ensue. As soon as there is a communication from the third-party developer to purchasers that the algorithm helps to align prices, this could possibly be enough to prove a violation under Article 101 (1) TFEU.[33] At the same time, the fact that these third-party pricing algorithms will have stochastic elements, and might be used to implement different pricing strategies determined by the final user might actually not lead to any pricing alignment (Schwalbe 2019; Dorner 2021).

5.4 *Collective Dominance*

If there would be increasing evidence of collusive outcomes on markets where algorithmic pricing has become widespread, Article 102 TFEU could also potentially provide an avenue for imposing antitrust law sanctions. Article 102 TFEU prohibits "[a]ny abuse by one or more undertakings of a dominant position within the internal market or in a substantial part of it [. . . .] so far as it may affect trade between Member States". While this provision has most often be applied to a single dominant undertaking, it also prohibits abuse of dominance by several undertakings that collectively hold a position of dominance.

The standard of proof of showing that there is collective dominance has somewhat converged with the requirement of showing coordinated effects or, in other words the likelihood of tacit collusion, from mergers (Mezzanotte 2010; Petit 2012; Jones et al. 2019, p. 284). In order to show that the conditions of collective dominance (or coordinated effects from a merger) can be established and sustained, the EU General Court established in the *Airtours* case three necessary conditions[29.34] First, the degree of transparency on the given market needs to be high so to allow market players to monitor each other's conduct. Second, there needs to be a retaliation mechanism in place that is capable of deterring or punishing deviating conduct, i.e. the undercutting of prices. Third, neither customers nor potential competitors could counteract the collusive strategy. The existence of buyer power, for example could be a factor that would undermine tacit collusion.

In addition, there needs to be an abuse to establish a violation of Article 102 TFEU. Article 102 (a) TFEU gives as an example of abuse "directly or indirectly imposing unfair purchase or selling prices or other unfair trading conditions". If the conditions of collective dominance could be established through pricing algorithms, the charging of supra-competitive prices could then constitute abuse for being an

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[33] Along similar lines, see Case C-74/14 *Eturas and Others.*

[34] Case T-342/99 *Airtours*. See also EU Commission (2004). Horizontal Merger Guidelines, 2004/C 31/03, 45–57.

unfair price. So far, however, there is very little case law on unfair prices in the EU, and even less so on unfair prices as a collective abuse of dominance (Jones et al. 2019, p. 696).

6 Comparative Legal Analysis of Algorithmic Pricing Situations

When it comes to the assessment of algorithmic pricing, the application of antitrust law both in the US and the EU turns on an appreciation of whether there is coordination by agreement or non-agreement coordination. Easy cases arise where algorithms are deployed by express agreement between competitors, with a design to coordinate price or other competitively sensitive terms. This should in all cases be illegal *per se* (US Law) or a restriction of competition by object (EU law) and, as in the Amazon posters cases, subject to criminal prosecution and appropriate private enforcement.

In the case of coordination by algorithm, just as with non-algorithmic coordination, a proof problem arises. Observed coordination may be by agreement, giving rise to *per se* treatment (above), or by non-agreement, leading both to questions (1) whether non-agreement coordination aided by algorithms is somehow different, and (2) whether coordination by algorithms can rise to the level of agreement, even if not originally animated by agreement. As to this second question, under the current state of US antitrust law, the mere deployment of an algorithm which, through machine learning, engages with another algorithm through a series of exchanges and commitments that can be likened to "agreement," is unlikely to give rise to liability. This situation is similar in the EU, albeit price signaling by pricing algorithms could under certain circumstances be interpreted as a form of concerted action. This is one place where experience and empirical study may highlight features of algorithms that are inconsistent with competitive outcomes, providing a basis for enforcement that does not currently exist. The incremental evidence that is building up from experiments run e.g. by Calvano et al. (2019, 2020) and the Swedish Competition Authority (Konkurrensverket 2021), and others, which try to approximate, step-by-step, real market conditions in which AI pricing tools are deployed are an important component. For now, as oligopoly theory would predict, the symmetry of agents is a factor conductive to collusion, but as the Swedish Competition Authority shows, it is not a necessary condition for algorithmic tacit collusion to arise (Konkurrensverket 2021). In addition, traditional factors in competitive analysis as, e.g., entry barriers remain valid with algorithms: when the algorithm can take threat of entry into account, prices will be lower (Konkurrensverket 2021). All initial evidence seems to point in the direction that cases of algorithmic collusion will have to be treated on a case-by-case basis. Their evaluation will be highly dependent on the strategies or policies programmed into or developed by the algorithms.

As to the first question above, the concerns for coordinated outcomes requires an analysis of how to analyze algorithmic pricing. The remedial problem animating the historic debate over challenging non-agreement coordination is equally relevant in the context of non-agreement coordination through algorithms. The more draconian remedies available under US law, including criminal penalties and treble-damages liability, would be inappropriate if applied to an independent decision to deploy a pricing algorithm. Likewise, analysis under the rule of reason would be appropriate, leaving the burden of showing both harm to competition and—where appropriate—the possibility of a less restrictive alternative, on the agency or private enforcer. Sanctions in government enforcement in this case should be limited to forward-looking injunctive relief (Huffman 2022a). In EU law, with its main focus on public competition enforcement, less radical sanctions could be imposed. Cases involving algorithmic pricing could be initially settled by commitments,[35] wherein the EU Commission could impose behavioral remedies or request changes to algorithmic design. In this way the EU's public enforcement approach, applying more of a regulatory than adversarial lens (Huffman and Schmidt-Kessen 2021), is a better fit for the current state of uncertainty with regard to the novel technologies at issue.

Even under a cautious enforcement approach, however, what forward-looking injunctive relief might be appropriate is unclear. Much as Turner (1962) argued, a prohibition of independent profit-maximizing behavior is problematic. The most promising intervention is to challenge features of pricing algorithms that implicate the most concerning of the facilitating practices, whether information sharing or other, identified by Clark (1983), Dibadj (2010), and Page (2017). Disclosures of competitively sensitive information, whether by human or by algorithm, are correlated with coordinated outcomes and should be subject to challenge, with questions of temporality (future, present, or past) and breadth (public or disclosed to competitors only) animating the analysis. Where those disclosures happen by agreement, they should ordinarily be subject to challenge. Other agreements that increase homogeneity or transparency, facilitating non-agreement coordination by algorithm, are likewise concerning. Cooperation among competitors in selecting and programming an algorithm should be considered a facilitating practice and subject to a high degree of scrutiny, likely leading to a challenge—although as with other discussions of business practices, there may be efficiency justifications that will need to be indulged. As empirical results become available to support this, courts and enforcers should be open to interposing presumptions, shifting the burden to justify a particular use to the firm employing an algorithm.[36] Efficiency consideration would equally play a role under EU competition law, both to determine whether the deployment of algorithmic pricing should be categorized as a restriction of competition by effect under Article 101 (1) TFEU (which would require showing of

[35] Article 9 Regulation 1/2003.

[36] This is an application of what in the US system is called the "quick look" or "abbreviated rule of reason."

anti-competitive effects on the market from the conduct) and whether it can benefit from an efficiency exemption under Article 101 (3) TFEU.

Merger review provides an opportunity to check changes in market structure or other impacts that may facilitate coordination by algorithm, which is otherwise not subject to challenge under the Sherman Act. In the US, such review should follow the existing analysis outlined in *Horizontal Merger Guidelines* Section 7. In particular, structural presumptions exist as a check on concentration levels (*Guidelines*, section 7.2). As empirical evidence is developed, it is possible those presumptions will need to be strengthened if the arguments of Gal (2019) that algorithmic pricing leads to collusion more readily than non-algorithmic pricing prove to be accurate. Mergers in markets with a history of collusion or non-agreement coordination are already subject to scrutiny based on that history (*Guidelines*, section 7.2), and in the case of markets characterized by pricing algorithms enforcers should investigate whether algorithms were adopted as a means to facilitate coordination and whether past practice with algorithmic pricing in that industry led to outcomes causing concern. Mergers that tend to eliminate the "maverick," perhaps the firm that continues not to employ industry standard software in its pricing decisions or perhaps the firm that programs its software to compete more aggressively than the industry norm, should be subject to increased scrutiny on that basis as well (*Guidelines*, section 7.2).[37] Reflecting the substantial convergence of merger enforcement policy, the same reasoning would apply under the EU Merger Regulation (Akman and Garrod 2011).[38]

Under EU law, the problems addressed under merger law could alternatively be dealt with under and abuse of collective dominance under Article 102 TFEU. This would allow competition authorities to intervene also in the absence of a merger, but it would require a competition enforcer to show that the market in question has the structural conditions that are thought to be conductive to collusion under the *Airtours* criteria discussed above. If, in the case of a concentrated market, pricing algorithms indeed contributed to more transparency, and there was no significant buyer power or other countervailing factor, the question whether algorithms could engage in retaliation in cases of price cuts would define whether collective dominance can be established. For this to happen, algorithms would likely need to be relatively simple and would need symmetric learning capacities to potentially be able prove a position of collective dominance. The question would then still remain whether there is collective abuse and at which level supra-competitive prices would become unfair prices under Article 102(a) TFEU.[39] In the US, collective dominance, or "shared monopoly,"as a theory of harm has not been seriously considered in more than 40 years; one question will be whether the

[37] *E.g.*, *United States v. H&R Block Inc.*, 833 F. Supp. 2d 36 (D.D.C. 2011).

[38] See Regulation 139/2004 and EU Commission (2004). Horizontal Merger Guidelines 2004/C 31/03.

[39] On the difficulty of establishing unfair prices.

efficiency of algorithmic decisions might provide a basis for re-examining such a theory in the coming years.

Given the greater constraints of the Sherman Act relative to Articles 101 and 102 TFEU, a US-law analog is the so-called "stand-alone" action under FTC Act section 5 challenging conduct as an "unfair method of competition." Resort to the FTC Act is a common solution advocated by scholars identifying concerns not subject to challenge under existing law of Section 1 (e.g., Dibadj 2010, pp. 606–608). Such an approach is most frequently identified with the FTC's *Ethyl Corp.* Prosecution.[40] *Ethyl Corp. w*as reversed on appeal to the federal court of appeals, which held that independent unilateral conduct by firms did not violate the FTC Act, partly on the basis of insufficient proof of an instance of conduct that led to the observed outcomes. The possibility of identifying adoption of algorithmic terms empirically shown to be uniquely pernicious as a way to satisfy the court of appeals' requirement remains.

7 Voices of Policy Makers and Future Outlook

The issue of algorithmic collusion has not escaped the attention of enforcers and policymakers. Broadly summarized, policy responses, in public reports or submissions to multi-jurisdictional committees, reflect both (1) confidence in existing antitrust rules to attack anti-competitive practices and outcomes caused by use of algorithms, and (2) caution with regard to novel theories of enforcement in the absence of real-world evidence of harm caused by the adoption of algorithms. Based on the strength of the theoretical concerns, but the weak evidence of real-world effects, the right approach will continue to be watchful caution on the part of enforcers and policymakers, who should seek to develop evidence of market-level effects to develop their regulatory toolkits. In addition, the current state of substantial parity of analysis across jurisdictions presents a unique opportunity for inter-jurisdictional cooperation.

Existing communications can be described as more, moderately, and less aggressive in their analysis and anticipated treatment of algorithmic pricing. The Autoridade da Concorrência (2019) report on *Digital Ecosystems, Big Data and Algorithms* may be the most suggestive of need for oversight and intervention. With regard to the most dramatic concerns, exemplified by the laboratory experience of Q-learning algorithms "colluding" without active human intervention, *Digital Ecosystems* correctly notes this has not been shown to have happened in a real-world context, but careful attention is appropriate (Autoridade da Concorrência 2019, pp. 270–275). In particular, *Digital Ecosystems* notes firm responsibility for

[40] *In re Ethyl Corp.*, 101 F.T.C. 425 (1983), *reversed*, *Ethyl Corp. v. FTC*, 729 F.2d 128 (2d Cir. 1984).

effects caused by algorithms they deploy and the possibility of requirements to test and verify to ensure compliance (Autoridade da Concorrência 2019, pp. 274–275).

The UK Competition and Markets Authority (CMA) published a Report in 2021 on Algorithms (CMA 2021). On the issue of possible risks for markets from algorithmic tacit collusion, it concluded that empirical evidence is so scarce that no clear conclusions can be drawn. The report by the French Autorite de la Concurrence and Bundeskartellamt (2019) on *Algorithms and Competition* predicts the success of existing rules and enforcement approaches in most cases, and identifies a lack of evidence for the autonomous coordination concerns, recognizing also that tacit collusion is not subject to challenge under EU law (Autorite de la Concurrence and Bundeskartellamt 2019, pp. 26–60). In summary remarks, *Algorithms and Competition* states that existing competition law regimes are sufficient for the task, prior cases involving algorithms have not taxed authorities' expertise, and legal changes should wait for a clearer picture of the types of cases that may be encountered in the future (Autorite de la Concurrence and Bundeskartellamt 2019, p. V). The Canadian Competition Bureau was an early mover with its discussion paper, *Big Data and Innovation* (2017), where it highlighted concerns for post-merger coordination, perhaps from the acquisition of a maverick, and increased transparency through facilitating practices (Competition Bureau Canada 2017, pp. 20–21). However, the CCB did not see any intervention short of price control that would be appropriate (Competition Bureau Canada 2017, pp. 20–21) and instead noted the enforcement experience where traditional cartel agreements were reached using digital tools, including algorithms programmed by agreement between the cartelists (Competition Bureau Canada 2017, pp. 19–21).

The so-far limited reaction from the US is the least suggestive of need for intervention. In 2018, the US antitrust agencies cooperated in a report to the OECD Competition Committee in which they highlighted their views on algorithmic collusion.[41] The US agencies noted the scholarly interest in collusive outcomes reached by algorithm, and noted one of the particular features – speed of response and adjustment – frequently highlighted in those scholarly analyses (DOJ/FTC OECD, para. 18).[42] Substantial shifts in enforcement priorities following political change (Huffman 2022b, pp. 4–6, 6, 8–9) can be expected to bring a different lens to the problem, but we are still lacking definitive pronouncements showing revised goals.

Multi-jurisdictional committees have much promise in facilitating cooperative development of expertise and rules. Both the OECD and ICN have been engaged in the question of coordination by algorithm. For example, the OECD *Algorithms and Collusion Report* (2017) canvassed literature and enforcement experience with

[41] Implications of E-commerce for Competition Policy - Note by the United States, at paras. 18–20 (6 June 2018).

[42] An extensive report by a committee of the US Congress considered algorithms only by reference to concerns for dominance and did not discuss the impact of algorithmic pricing on coordinated outcomes. *See* Judicary Report (2020).

regard to collusive outcomes reached by algorithm and observed, “algorithms may permit firms to replace explicit collusion with tacit co-ordination.” (OECD 2017, section 4.3). In light of this concern, the OECD *Report* highlighted the possibility of “revisiting” “the notion of agreement”, possibly considering rapid price adjustment leading to monopoly outcomes to be treated as “agreement”, as could parallel pricing by algorithms which acts as a signaling device (OECD 2017, section 5.2). In a scoping paper, “Big Data and Cartels” (2020), the ICN identifies the same concerns for non-agreement coordination, based on rapid repeated transactions, as well as the unproven possibility of deep-learning algorithms achieving computerized agreement, and also poses the question whether definitions of agreement need to be revised when algorithms operate autonomously (ICN 2020, pp. 12–17).

Moving early to distill the state of the learning to amendments to guidelines promises benefits. It will enable counsel to better advise firms on their deployment of increasingly sophisticated software. As one example, the Competition Bureau of Canada’s newly revised *Competitor Collaboration Guidelines* (2021) recognizes “agreements between competitors to use a common pricing algorithm” as a cartel agreement, adding the caution that “conduct that amounts to conscious parallelism is not sufficient (Competition Bureau Canada 2021, section 2.4.1 & n.15). Empirical research into the effects of pricing algorithms, taking into account both the substantial efficiency benefits and the well-theorized concerns, should be a first priority investment for agencies or multi-jurisdictional groups, perhaps through grants to research teams. Much agency expertise is developed through case investigation and prosecution, and studying the effects of algorithmic pricing as part of merger and non-merger investigations should be a priority. Those agencies that have powers to carry out sector inquiries, like the EU Commission[43] and the National Competition Authorities in the EU Member States, as well as the analogous US FTC Section 6 authority (US Federal Trade Commission 1981),[44] could use these powers to acquire more evidence about the state of the art of pricing algorithms and their market impact (Konkurransetilsynet 2021).[45] Enforcement efforts raising these issues should include technologists to complement the existing reliance on economic and management expertise. After greater experience and understanding is developed, rulemaking or legislation targeting the most pernicious uses of technology, likely to be those that produce transparency among competitors but not in the market generally, should be on the table.

[43] Article 17 Regulation 1/2003.

[44] United States Code, Title 15, Section 46. Page (2009) outlines this procedural advantage that is unique to the FTC in US law.

[45] A recent example of such a sector inquiry is a recent Report by the Norwegian Competition Authority surveying the use of monitoring and pricing algorithms on Norwegian markets.

8 Conclusion

Substantial scholarly attention and, more recently, work by enforcers and policy-makers in understanding the effects of broad deployment of algorithms to establish prices has not produced a definitive resolution of the degree of the concern or the nature of the appropriate intervention. Both sides—technical development of pricing software, and the establishment of toolkits for investigation and enforcement, continue to develop. In this chapter we bring to the front several key areas of interest for scholars, advocates, and enforcers.

The question of the impact of algorithmic pricing on market outcomes remains unresolved. Theories advanced by early movers among scholars including Mehra, Ezrachi, Stucke, and Gal, have been broadly recognized as worth serious attention by antitrust authorities and policy-makers. The more challenging questions related to autonomous discovery and response, leading in laboratory experiments to algorithmic collusion, are today not sufficiently proved empirically in real-world settings to give rise to more than cautious concern. Empirical findings are also lacking as to the net effect on competition and consumers of efficiency-enhancing algorithmic decision-making, which also threatens coordinated outcomes. Additional empirical evidence from laboratory and real-world experiments, taking into account the diversity of algorithmic design and the variety in the data sources that could be deployed in the development of algorithmic pricing strategies, is necessary. In particular, a better understanding of the incentives and strategies of developers and adopters of pricing algorithms will improve responses in competition policy and law.

An important observation from our comparative study is the substantial parity in treatment across leading antitrust systems. Jurisdictions on both sides of the Atlantic broadly dislike coordinated outcomes, but recognize the challenge or impossibility of preventing these, if no actual agreement between parties can be proven under the cartel prohibitions (Section 1 and Article 101 TFEU). There are less trodden paths that could be pursued by antitrust enforcers in the US and EU, on the one hand under Section 5 of the FTC Act or through Article 102 TFEU and collective dominance. Nonetheless, without having a sufficient evidence base that would specify if, how, and when pricing algorithms cause competitive harm, it seems premature to consider these potential avenues for antitrust enforcement.

Lastly, the overall observed parity provides substantial opportunity for cross-jurisdictional cooperation in finding successful strategies to combat harm that the law has not historically addressed. Prioritizing these concerns, and employing a mix of study, investigation, prosecution, and reduction to guidelines and law, are the right approaches to ensure both technological innovation and enforcement serves society's interests.

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