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ARTICLE

Overcoming the Current Knowledge Gap of Algorithmic "Collusion" and the Role of Computational Antitrust

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Abstract. Digital markets are evolving rapidly, and pricing algorithms are becoming prevalent. While they provide many benefits, there is a real threat of new harms and new challenges for antitrust authorities. Computational modelling has demonstrated these risks by showing that in many instances self-learning pricing algorithms lead to collusive outcomes. However, so far there has been woefully little empirical research into the dynamics of pricing algorithms. To provide context for this threat, we first review the usage and types of algorithmic pricing systems and critically examine the established taxonomy of algorithm-based collusion scenarios. We then describe how cartel screening techniques can be applied to algorithmic systems and the consequential logistical challenges and uncertainties. We propose action points needed to fill the knowledge gap.

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I. Introduction

Algorithms are playing an increasingly important role in many markets. In the "E-commerce Sector Inquiry" the European Commission reported that the majority of online retailers track online prices from their competitors, and, in doing so, two thirds use automated software.[1] In 2016, Chen et al. analyzed the top 1,641 best-selling products on the Amazon Marketplace and identified that 500 sellers used automated pricing software, based on the high frequency of price changes and their correlation with other sellers. These could only be achieved using automated systems. According to these authors, the sellers who used automated pricing received more positive feedback from consumers and won the Buy Box more frequently than their non-algorithmic counterparts, suggesting algorithmic sellers obtained higher sales volume and revenue.[2] On Amazon the "Buy Box" is a prominent section on product pages that allows users to add an item to their cart or make an instant purchase. When there are multiple potential sellers, an algorithm is used by Amazon to select which one will be featured based on price, seller rating, and other factors such as order defect rates and inventory volume.[3] The Buy Box is responsible for 80-90% of sales, so being consistently selected and winning the Buy Box gives sellers a significant competitive edge. The UK Competition and Market Authority (CMA) reports that for large Amazon sellers (over $1,000,000 in annual revenue) automated pricing software is considered essential.[4]

The adoption of algorithms is not limited to e-commerce. Automated (algorithmic) pricing is being implemented in many business areas. In general, there are three main situations where automated pricing is beneficial.[5] Firstly, in areas such as insurance or credit, the cost to serve customers can vary considerably but can be estimated algorithmically using observable data. Secondly, in areas where demand fluctuates rapidly such as taxi fares, airline fares or hotel room pricing, algorithms

[1] Eur. Comm'n, *Final report on the E-commerce Sector Inquiry*, at 31, COM (2017) 229 final (May 10, 2017), https://competition-policy.ec.europa.eu/document/download/e0e38b2e-7ef5-4a87-8245-fc19cbd0ab5d_en?filename=2017_ecommerce_SI_final_report_en.pdf.

[2] Le Chen et al., *An Empirical Analysis of Algorithmic Pricing on Amazon Marketplace*, PROCEEDINGS OF THE 25TH INTERNATIONAL CONFERENCE ON WORLD WIDE WEB (2016), https://dl.acm.org/doi/10.1145/2872427.2883089.

[3] Emily Sullivan, *Winning the Amazon Buy Box [Algorithm Tips for 2024]* (2024), https://tinuiti.com/blog/amazon/win-amazon-buy-box/.

[4] Competition & Mkts. Aut., *Pricing Algorithms – Economic Working Paper on the Use of Algorithms to Facilitate Collusion and Personalised Pricing* 18 (2018), https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/746353/Algorithms_econ_report.pdf.

[5] Oxera Consulting LLP, *When Algorithms Set Prices: Winners and Losers*, DISCUSSION PAPER, 2 (2017).

can be used to react rapidly to the changing conditions.[6] Finally, automated pricing is convenient for vendors who have a wide range of products to price.

Pricing algorithms used by sellers thus react rapidly to changes in the market environment,[7] enable consistent pricing strategies, and reduce costs by automating decisions.[8] In this way, pricing algorithms can improve the allocation of resources and are consistent with a dynamic, well-functioning market.[9] Automated data collection and processing allows organization to make faster and better decisions and markets more efficient. Pricing algorithms can provide better reaction to demand and reduce information asymmetry and "mispricing" by producers. This enables better inventory management and reduces the risk of perishable stocks going to waste.[10]

However, by increasing supply side market transparency and the ability of sellers to react to each other's pricing, these algorithms can also contribute to supra-competitive equilibria[11] if they "collude" by aligning prices instead of competing.[12] Algorithms can make collusive agreements more stable and, potentially, easier to initiate in the first place.

A stark example of pricing algorithmics enabling better coordination and signaling can be seen in the Albertan wholesale electricity market.[13] In 2013 Alberta's Market Surveillance Administrator (MSA) flagged up concerns that firms were "tagging" their otherwise anonymous bids to reveal their identities and allow firms to coordinate prices.[14] Machine learning algorithms had been able to predict the identity of a firm with an average accuracy of 86%. Following the MSA report suppliers appeared to randomize their bids, removing any overt patterns in price

[6] OECD, *Algorithms and Collusion: Competition Policy in the Digital Age* 16 (2017), https://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm.
[7] Robert M Weiss & Ajay K Mehrotra, *Online Dynamic Pricing: Efficiency, Equity and the Future of E-Commerce*, 6 VA. JL & TECH. 11 (2001).
[8] Competition & Mkts. Aut., *supra* note 4, at 21.
[9] OECD, *Algorithmic Competition*, OECD Competition Policy Roundtable Background Note 10-11 (2023), https://www.oecd.org/daf/competition/algorithmic-competition-2023.pdf.
[10] Competition & Mkts. Aut., *supra* note 4, at 20.
[11] Pricing above what can be sustained in a competitive market.
[12] Shen Li, Claire Chunying Xie & Emilie Feyler, *Algorithms & Antitrust: An Overview of EU and National Case Law,* CONCURRENCES E-COMPETITIONS ALGORITHMS & COMPETITION (2021), https://www.concurrences.com/en/bulletin/special-issues/algorithms-competition/algorithms-antitrust-an-overview-of-eu-and-national-case-law.
[13] David P Brown et al., *Information and Transparency: Using Machine Learning to Detect Communication between Firms*, 3 STAN. COMPUTATIONAL ANTITRUST 199 (2023).
[14] MKT. SURVEILLANCE ADMINISTRATOR, COORDINATED EFFECTS AND THE HISTORICAL TRADING REPORT: DECISION AND RECOMMENDATION 8, 8-15 (2013).

decimals. Nevertheless, despite an initial drop in accuracy, within three months the algorithm obtained average accuracy of 82%.[15]

However, is important to not lose sight of the social and consumer welfare enhancing effect that algorithms can provide, as blanket bans or other heavy-handed interventions risk doing more harm than good. Even algorithmically driven supra-competitive coordination may not lead to a reduction in consumer welfare. O'Connor and Wilson found that algorithms designed to reduce consumer demand uncertainty would expand the scope for collusion in situations where it would not otherwise be sustainable. This was because more accurate data collection and processing would allow companies to better differentiate between low sales volumes from demand shocks and those from firms undercutting an agreed cartel price. However, these systems would also make it easier to identify when there are greater payoffs for defecting. The authors found the overall effect on consumer welfare was ambiguous, as there were many instances where collusion was still possible, but companies could no longer sustain monopolistic prices.[16]

Algorithmic pricing may also lead to price discrimination in the form of personalized pricing. This is the practice of charging different customers different prices not justified by differences in costs, but instead based on observable features.[17] This typically improves social welfare, however the general effect of price discrimination on consumer welfare is ambiguous.[18] Companies use personalized pricing to try and capture as much consumer surplus as possible, but it can also intensify competition and lower overall prices.[19] By collecting personal data about consumers, algorithms can allow for even granular pricing schemes based on an individual's estimated willingness to pay.[20]

Models based on the assumption that firms are able to use tracking devices to collect data on their own customers show an increase in aggregate consumer surplus.[21] However, Dubé and Misra found that algorithmic personalized pricing

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[15] Brown et al., *supra* note 13.
[16] Jason O'Connor & Nathan E. Wilson, *Reduced Demand Uncertainty and the Sustainability of Collusion: How AI Could Affect Competition*, 54 INFORMATION ECON. & POL'Y (2021).
[17] Christopher Townley et al., *Big Data and Personalized Price Discrimination in EU Competition Law*, 36 YEARBOOK EUR. L. 683 (2017).
[18] *See* Frederik Zuiderveen Borgesius & Joost Poort, *Online Price Discrimination and EU Data Privacy Law*, 40 J. CONSUMER POL'Y 347 (2017).
[19] James C Cooper et al., *Does Price Discrimination Intensify Competition-Implications for Antitrust*, 72 ANTITRUST L.J. 327 (2004).
[20] Haggai Porat, *Algorithmic Personalized Pricing in the United States: A Legal Void*, CAMBRIDGE HANDBOOK ON PRICE PERSONALIZATION AND THE LAW (forthcoming).
[21] Chongwoo Choe et al., *Pricing with Cookies: Behavior-Based Price Discrimination and Spatial Competition*, 64 MGMT. SCIENCE 5669 (2018).

instead reduced total consumer surplus by 23% compared to uniform pricing, but over 60% of customers benefited from lower prices.[22] Personalized Pricing is an area of considerable debate,[23] which we do not explicitly address in this paper.

There is some debate as to whether the current US or EU competition regimes adequately address all instances of algorithmic collusion, particularly when the collusion arises autonomously from algorithms interacting, without intentional conduct, awareness, or communication between human competitors.[24] For the purposes of this paper, we leave open the issue of whether this kind of autonomous algorithmic conduct is unlawful. Instead we focus on the logistical problems of detecting and analyzing algorithmic pricing patterns, the current lack of empirical research in this area, and the technical and legal tools deployed by regulators.

This article is structured as follows. In Section II, we examine the usage of and types of algorithmic pricing systems, distinguishing between the relatively simple "rules based" systems and the more technologically sophisticated "machine learning" systems, and, in the case of the latter, "deep learning" systems. In section III we critically examine the now established taxonomy of algorithm-based collusion scenarios and argue it is more useful to divide these groups into two main categories, human relatable conduct, and purely automated conduct. In section IV and V we describe how screening techniques designed to detect collusion can be applied to algorithmic systems: section IV discusses the methods used to detect algorithmic conduct, while section V examines screening indicia. In section VI we look at the challenge of collecting the volume of data necessary to understand algorithm pricing software. We discuss what has been done to date and its limitations and offers suggestions for what needs to be done. Finally, in Section VII, we discuss the techniques for auditing algorithms themselves and some of the technical difficulties regulators face in doing so and we propose appropriate solutions.

[22] Jean-Pierre Dubé & Sanjog Misra, *Personalized Pricing and Consumer Welfare*, 131 J. OF POL. ECON. 131 (2023).

[23] *See* OECD, *Personalised Pricing in the Digital Era* (2018), www.oecd.org/daf/competition/personalised-pricing-in-the-digital-era.htm.

[24] *See* Joseph E Harrington, *Developing Competition Law for Collusion by Autonomous Artificial Agents*, 14 J. OF COMPETITION L. & ECON. 331 (2018); Stefan Thomas, *Harmful Signals: Cartel Prohibition and Oligopoly Theory in the Age of Machine Learning*, 15 J. COMP. L. & ECON. 159 (2019). Cf. Nicolas Petit, *Antitrust and Artificial Intelligence: A Research Agenda*, 8 J. EUR. COMPETITION L. & PRACTICE 361 (2017); Cento Veljanovski, *Pricing Algorithms as Collusive Devices*, 53 INT'L REV. INTELLECTUAL PROPERTY & COMPETITION L. (2022).

II. Algorithmic Pricing Systems in Practice

Many online marketplaces, such as Amazon, eBay, Shopify, Walmart and Google Shopping, provide inbuilt tools for automated price adjustments by implementing pricing rules with pre-set triggers. For example, on the Amazon Marketplace, a vendor could create a price rule designed to automatically undercut the Buy Box price (the price of the current winner of the Buy Box) by a fixed amount until they win the Buy Box or reach a specified minimum.[25]

There is also a growing market for third party repricing services that can offer more sophisticated or finer pricing controls, such as ChannelEngine, RepricerExpress and Informed.co.[26] These services allow for greater flexibility, such as price-matching to specific competitors, or switching between multiple pricing strategies depending on market conditions. These services often advertise themselves on their ability to more reliably win the Buy Box while maximizing profit margins.

Pricing algorithms can be divided into two broad categories: "fixed" or "rule-based" algorithms that depend on human-selected rules and parameters, and those that instead rely on machine learning techniques that automatically change and adapt over time in an attempt to maximize the seller's long-term profits.[27] Examples of the former include Repriceit or ChannelMAX. Examples of the latter include Feedvisor and WisePricer.[28]

There are three main types of rule-based pricing.[29] Competition-based pricing is the most commonly used strategy and allows sellers to create rules that will adjust their selling price based on the actions of their competitors, such as the price matching or undercutting techniques described above. The second type, sales-based pricing, depends instead on changes in sales volume. For example, Amazon's inbuilt sales tools allow sellers to impose pricing rules that will automatically decrease prices if sales volumes drop below a certain threshold.[30] Finally, there are time-based pricing features rules where price changes are dependent on the time of day, or day of the

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[25] AMAZON, AUTOMATE PRICING, https://sellercentral.amazon.com/help/hub/reference/external/G201994820.

[26] Qiaochu Wang et al., *Algorithms, Artificial Intelligence and Simple Rule Based Pricing* (2022), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4144905.

[27] Emilio Calvano et al., *Algorithmic Pricing: What Implications for Competition Policy?*, 55 REV. INDUS. ORG. 155 (2019).

[28] Dana Popescu, *Repricing Algorithms in E-Commerce*, Working Paper No. 2015/75/TOM INSEAD (2015), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2669997.

[29] Wang et al., *supra* note 26.

[30] AMAZON, CREATE A SALES-BASED PRICING RULE, https://sellercentral.amazon.com/help/hub/reference/external/FRJDFLFPWZSAG67.

week. For example, RepricerExpress features a "sleep mode" which can be used to reset prices to a pre-set maximum overnight in an attempt to reset any pricing wars against competitors using pricing algorithms set to undercut the seller.[31] Table 1 provides an overall summary of the available third-party repricing systems.

Algorithm Type	Provider	Example
Competition-based	Alpharepricer, Aura, ChannelAdvisor, ChannelMAX, Informed.co, SellerEngine, RepricerExpress, Repriceit, SellerActice	Setting prices to marginally undercut the lowers price on the market
Sales-based	Alpharepricer, ChannelMAX, SellerEngine, SellerActive	Decreasing prices if the volume of sales drop
Time-based	ChannelMAX RepricerExpress, Repriceit	Resetting prices to maximum values during low sale periods
Machine Learning based	Alpharepricer, Aura, Feedvisor, Informed.co, WisePricer	Black box decision making rules

Table I: Repricing Algorithm Types.

There are three main categories of machine learning systems: (a) supervised learning, where the algorithm uses a sample of labelled data to learn a general rule that maps inputs to outputs; (b) unsupervised learning, where the algorithm attempts to identify correlations and patterns from unlabelled data; and (c) reinforcement learning, where an algorithm performs actions in a dynamic environment and learns through trial and error.[32]

Third party commercial repricing software providers typically do not divulge the machine learning techniques used, but most experimental computer science

[31] REPRICEREXPRESS, USING THE SLEEP MODE TO AVOID A PRICE WAR, https://support.repricer.com/sleep-mode.
[32] Competition & Mkts. Aut., *supra* note 4, at 11.

literature uses reinforcement learning.[33] To function, a reinforcement learning algorithm must receive data about the state of the environment, be able to take actions that then affect the state and have a goal relating to said state. When the algorithm executes actions, it receives feedback in the form of a "reward signal" and based on this the algorithm seeks to learn what actions maximize the expected cumulative reward. Many reinforcement learning algorithms involve estimating "value functions", which is the expected long-term reward of a given action. Use of value functions allows the algorithm to learn the benefit of taking actions that offer little (or even negative) immediate reward, but which have a larger long-term payoff.[34] Rather than being provided with hardcoded rules such as "always undercut the cheapest rival by X% down to the pre-set minimum price," the algorithm develops its own decision-making rules.

An important subset of machine learning is "deep learning". While traditional machine learning algorithms can only be applied to linearly separable data, deep learning algorithms can learn any arbitrary function.[35] Deep learning algorithms involve a "neural net" composed of multiple layers of simple processing units that mimic the behaviour of human neurons.[36] There will be an input layer, one or more hidden layers (defined as a layer that is neither input or output), and an output layer. To qualify as "deep learning," the network must have at least two hidden layers.

The input layer does not process information, the output of each neuron is simply the value of the data stored. Each input layer neuron then sends this value of each of the first hidden layer neurons. Each hidden layer neuron then processes this information and sends an output value to each of the neurons on the next layer, and so on.[37] Each connection between neurons has an associated weight, which is adjusted as the network learns, and the output of each neuron depends on the weighted sum of all inputs. The values of the output layer neurons will have some meaning which corresponds to the task the network is designed to perform, but the output of neurons in the hidden layer may not have any meaningful interpretation.[38] Because of this, it can be difficult to interpret the decision-making process of a deep learning

[33] *See* Ludo Waltman & Uzay Kaymak, *Q-learning Agents in a Cournot Oligopoly Model*, 32 J. ECON. DYNAMICS & CONTROL 3275 (2008); Emilio Calvano et al., *Artificial Intelligence, Algorithmic Pricing, and Collusion*, 110 AM. ECON. REV. 3267 (2020).
[34] RICHARD S. SUTTON & ANDREW G. BARTO, REINFORCEMENT LEARNING: AN INTRODUCTION 6-13 (ed. 2018).
[35] MICHAEL A NIELSEN, NEURAL NETWORKS AND DEEP LEARNING ch. 4 § 25 (2015); Yann LeCun et al., *Deep learning*, 521 NATURE 436 (2015).
[36] IAN GOODFELLOW et al., DEEP LEARNING pt 1.2 (2016).
[37] *See* HOWARD B DEMUTH, et al., NEURAL NETWORK DESIGN 44-48 (2014); Saurabh Karsoliya, *Approximating Number of Hidden Layer Neurons in Multiple Hidden Layer BPNN architecture*, 3 INT'L J. ENGINEERING TRENDS & TECH. 714 (2012).
[38] JOHN D KELLEHER, DEEP LEARNING 67-76 (2019).

algorithm.[39] Given a particular set of inputs, the outputs or decision reached can be observed, but it can be difficult to determine how the network reached this outcome, or even which parts of the input data most strongly influenced the final decision. As such, deep learning networks are often described as opaque "black boxes" that "hide their internal logic to the user."[40]

III. Legal Taxonomy of Potential Collusive Scenarios

While algorithmic pricing promises many advantages, since 2015 legal scholars and policy makers have expressed concerns that algorithmic pricing software may also facilitate collusive behavior.[41]

There are several mechanisms that have been proposed to explain how and why algorithms could lead to collusive outcomes. They generally fall into four main categories. Firstly, algorithms make it easier and cheaper to monitor a collusive agreement, and respond more rapidly to any deviations. Secondly, algorithms can more reliably implement a collusive agreement, with a reduced risk of errors or agency slack.[42] With a greater volume of information about demand conditions and competitor prices, firms are less likely to confuse a period of low demand with a cartel partner cheating. Improved analytical power also allows better demand prediction, as well as predicting rival actions.[43] Thirdly, algorithms may be able to signal more effectively, by being able to send signals indicating a short term commitment to a particular pricing strategy that are either too brief or are sent at periods of low demand and so do not impact sales, but that can be detected by monitoring algorithms.[44] They may also be designed to react predictably, in a way that can reduce strategic uncertainty.[45]

Ezrachi and Stucke identified four scenarios in which algorithms could lead to collusion.[46] The first, "messenger", is when algorithms are used to more reliably

[39] Madalina Busuioc, *Accountable Artificial Intelligence: Holding Algorithms to Account*, 81 PUBLIC ADMIN. REV. 825 (2021).
[40] Riccardo Guidotti et al., *A Survey of Methods for Explaining Black Box Models*, 51 ACM COMPUTING SURVEYS 1 (2018).
[41] *See* Salil K Mehra, *Antitrust and the Robo-Seller: Competition in the Time of Algorithms*, 100 MINN. L. REV. 1323 (2015). OECD, *supra* note 9.
[42] Competition & Mkts. Aut., *supra* note 4, at 23-25.
[43] Michal Gal, *Limiting Algorithmic Coordination,* 38(1) BERKELEY TECH. L. J. (forthcoming).
[44] OECD, *supra* note 9, at 24-32.
[45] Competition and Markets Authority, *supra* note 4, at 25; Autorité de la Concurrence & Bundeskartellamt, *Algorithms and Competition* 38-39 (2019), https://www.autoritedelaconcurrence.fr/fr/communiques-de-presse/algorithmes-et-concurrence-lautorite-et-le-bundeskartellamt-publient-une.
[46] ARIEL EZRACHI & MAURICE E. STUCKE, VIRTUAL COMPETITION 36-37 (2016).

implement and monitor explicit cartel schemes. The second, "Hub and Spoke", involves firms relying on a common third-party provider of pricing algorithms. "Predictable Agent" posits firms unilaterally adopting algorithms deliberately designed to facilitate tacit collusion, while "Digital Eye" goes one step further and raises the prospect that self-learning algorithms tasked with the goal of profit maximisation may autonomously and independently converge on collusive outcomes without ever being explicitly programmed to do so.

However, from a legal and operational perspective, we consider that it is necessary to divide algorithmic collusion scenarios into two main categories: human-relatable conduct, and purely automated conduct. The former covers situations where algorithms are used to facilitate or coordinate traditional collusive practices and incorporates the "Messenger" scenario. The latter covers collusion in the absence of any prior or ongoing communication between human representatives and incorporates the "Predictable Agent" and "Digital Eye" scenarios. Depending on the context, the "Hub and Spoke" scenario may straddle the line between the two. This taxonomy is based on the principles of legal liability and attribution, and allows for a clearer categorization for policy making and law enforcement purposes.

The *Topkins* case in the US is a clear example of human relatable conduct. Here, several sellers conspired to fix the price of posters on the Amazon Marketplace and agreed to adopt pricing algorithmic software to implement the scheme. One of the competitors programmed an algorithm to find the lowest third party price offered by a third party and set their price just below that, while the conspirators had an algorithm programmed to match their co-conspirator's price.[47]

In the UK *Posters* case, Trod and GB Eye also agreed not to undercut one another for prices on posters and frames. Both sellers configured their algorithm to compete aggressively against sellers outside of the scheme and rapidly respond to changes in market conditions but would deliberately ignore each other's prices.[48]

In 2018 the European Commission fined Asus €63,522,000 for imposing a fixed or minimum release price for online retailers for a range of consumer electronics.[49] The Commission found that Asus relied on internal software monitoring tools to identify retailers that were selling their products below the desired level. The Commission also highlighted how the use of automatic pricing software by retailers

[47] *United States v Topkins*, No. CR 15-00201, 2015 (N.D. Cal. Apr. 30, 2015); Salil K Mehra, *US v. Topkins: Can Price Fixing Be Based on Algorithms?* 7 J. EUR. COMPETITION L. & PRACTICE 470 (2016).
[48] Decision of the Competition & Mkts. Aut. in case no. 50223: Trod Ltd/GB Eye Ltd (Aug. 12, 2016).
[49] Eur. Comm'n, *Antitrust: Commission Fines Four Consumer Electronics Manufacturers for Fixing Online Resale Prices* (2018), https://ec.europa.eu/commission/presscorner/detail/en/IP_18_4601.

amplified the effect of Asus's interventions. The pricing algorithms used by the retailers were designed to price match, so by targeting the lowest pricing retailers Asus could prevent a more general price erosion.

The "Hub and Spoke" category includes situations which are similar to, but would not necessarily actually qualify as, classic hub-and-spoke cartel arrangements.[50] The case of *Eturas* in the EU has been cited as an example of an algorithmic "Hub and Spoke" situation under Ezrachi and Stucke's taxonomy.[51] However, while it did demonstrate similar structure and technical implementation, this case was not legally considered to be an instance of conventional hub-and-spoke collusion.[52] In *Eturas*, Lithuanian travel agents used a common third-party booking software. The administrator of the software then proposed a rule that would limit the maximum allowable discount that could be applied via the booking system. The European Court of Justice found that this would constitute a concerted practice under Article 101 TFEU if it could be shown that the travel agencies were aware of the message.[53]

Ezrachi and Stucke confine the "Hub and Spoke" scenario to instances where competitors all use the same algorithms to determine market prices or market changes.[54] However the potential range of situations in which algorithmic collusion involves a third party is much broader. While the third party could be the provider of a common algorithm, it could also provide a means of exchanging data, or even a common data pool. Third parties could also coordinate the algorithms of competitors in other ways, such as an external consultant that advises companies in the same market on the design and use of algorithms.[55] The common feature is that there is no direct communication or contact between the competitors.

Whether this behavior would amount to human relatable conduct would depend on the awareness of the parties, as set out by the ECJ in *Eturas*. This division is also adopted by the Autorité de la Concurrence and Bundeskartellamt, which distinguish between situations where competitors knowingly coordinate via a third party, and

[50] A hub-and-spoke agreement occurs when a horizontal agreement is implemented without any direct communication between the competitors but is facilitated by agreements with a vertically related common third party. *See* RICHARD WHISH & DAVID BAILEY, COMPETITION LAW 337-340 (7th ed. 2012).
[51] EZRACHI & STUCKE, *supra* note 46, at 52-53.
[52] Opinion of AG Szpunar, Case C-74/14, "Eturas" UAB and others v. Lietuvos Respubilkos Konkutencijos Taryba, ECLI:EU:C:2015:493, ¶ 65 (July 16, 2015).
[53] Case C-74/14, "Eturas" UAB and others v. Lietuvos Respublikos Konkutencijos Taryba, ECLI:EU:C:2016:42 (Jan. 21, 2016).
[54] Ariel Ezrachi & Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition*, 5 U. ILL. L. REV. 1776 (2017).
[55] Autorité de la Concurrence & Bundeskartellamt, *supra* note 45, at 31.

those where they are unaware of the coordination, in that they do not know or could not reasonably foresee it.[56]

The CMA considers that scenarios where sellers use the same algorithm or data pool to determine prices present the most immediate risk[57] but to date there have been no successful enforcement actions. However, at the time of writing there are several ongoing investigations and lawsuits alleging third-party driven behavior. In *Gibson v. MGM* it is alleged that hotels in the Las Vegas strip used third party software to aggregate pricing strategy information, keeping room rental rates artificially high.[58] RealPage, a provider of a price setting algorithm for property owners, is currently under investigation by the United States Department of Justice over allegations that its software allows users to coordinate pricing. The software works by collecting information from users, including what rents they are able to charge tenants, which is then used to recommend prices. RealPage states that this data is aggregated and anonymized and denies any anti-competitive conduct.[59]

Purely automated conduct has not yet been tested in enforcement practice, but a growing body of theoretical studies and computer simulations suggest that collusive outcomes are a real possibility under certain market conditions.[60] Few papers have identified algorithmic collusion in an empirical setting, although in a study of the German retail gasoline market Assad et al. found that the adoption of pricing algorithms in a duopoly led to a margin increase of 28% when both rivals adopted algorithmic pricing, while when only one station adopted an algorithm there was no increase.[61] Brown and MacKay relied on modelling to show that the adoption of algorithmic pricing by the five large online over-the-counter allergy drug retailers in the United States led to a profit increase of 9.6% and a 4.1% reduction on consumer surplus compared to a non-algorithmic counterfactual.[62]

It is important to note, however, that if a competitor created an algorithm that was deliberately intended to collude, even a self-learning one such as the algorithm

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[56] *Id.* at, 32.
[57] Competition & Mkts. Aut., *supra* note 4, at 31.
[58] *Richard Gibson et al. v. MGM Resorts Int'l et al.*, 2:23-cv-00140-MMD-DJA (D. Nev. Oct. 24, 2023).
[59] Heather Vogel, *Department of Justice Opens Investigation into Real Estate Tech Company Accused of Collusion with Landlords*, PROPUBLICA (2022).
[60] Bruno Salcedo, *Pricing Algorithms and Tacit Collusion*, MANUSCRIPT, PENNSYLVANIA STATE UNIVERSITY (2015); Calvano et al., *supra* note 33; Timo Klein, *Autonomous Algorithmic Collusion: Q-Learning under Sequential Pricing*, 52 RAND J. ECON. 538 (2021).
[61] Stephanie Assad et al., *Algorithmic Pricing and Competition: Empirical Evidence from the German Retail Gasoline Market* (2020) CESifo Working Paper No. 8521 (2020).
[62] Zach Y. Brown & Alexander MacKay, *Competition in Pricing Algorithms*, 15 AM. ECON. J. 109 (2023).

demonstrated by Meylahn and den Boer,[63] this could constitute human related conduct.

It would appear, looking back, that Ezrachi and Stucke's fears have not been realized. As noted above, there have been relatively few enforcement actions since their book's publication. We postulate that this due to a combination of two main reasons.

Firstly, much of the technology was, at the time, speculative. Even today machine learning-based re-pricing systems are still in their infancy, although, as discussed in Section II, they are becoming increasingly commercially available. For the most part, companies are only now in a position to implement the systems that could lead to automated collusion.

Secondly, there is good reason to believe that detection will be extremely difficult. As will be discussed below in Section VI, analysis of algorithmic pricing systems requires the collection and processing of large quantities of pricing data. This presents obstacles for both regulators and academics. There have only been a handful of empirical studies, discussed in Section IV, exploring the behavior of pricing algorithms. While several authorities worldwide have developed systems for automatically collecting price data, most are limited to daily updates at most,[64] which therefore cannot capture high frequency price changes.

This is on top of the fact that cartel detection is inherently quite difficult. It has been estimated that the overall detection rate for cartels since World War 2 is between 10 and 30%.[65] A cartel screen can only flag up concerning behavior that has been previously identified from discovered and successfully prosecuted cartels. However, the set of discovered cartels may not be a representative sample of the overall population of cartels.[66] In the EU, between 1998 and 2017, over 90% of prosecutions came from leniency applications[67] and, as Schinkel points out, there is reason to believe that cartels successfully identified via leniency applications are

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[63] Janusz M Meylahn & Arnoud V. den Boer, *Learning to Collude in a Pricing Duopoly*, 24 MANUFACTURING & SERVICE OPERATIONS MGMT. 2577 (2022).
[64] *See* Thibault Schrepel & Teodora Groza, *The Adoption of Computational Antitrust by Agencies: 2nd Annual Report*, 3 STAN. COMPUTATIONAL ANTITRUST 55 (2023).
[65] John M. Connor, *Cartel Detection and Duration Worldwide*, 2 COMPETITION POL'Y INT'L: ANTITRUST CHRONICLE (2011).
[66] Joseph E. Harrington Jr. & Yanhao Wei, *What Can the Duration of Discovered Cartels Tell Us About the Duration of All Cartels?*, 127 ECON. J. 1977 (2017).
[67] Jerome De Cooman, *Outsmarting Pac-Man with Artificial Intelligence, or Why AI-Driven Cartel Screening Is Not a Silver Bullet*, 14(4) J. EUR. COMPETITION L. & PRACTICE 186 (2023).

liable to be the weakest, least stable cartels.[68] More sophisticated cartels that are resilient enough, or have otherwise developed ways to become leniency resistant, will not be detected. As will be discussed in Section V, there is reason to believe that algorithmic collusion may be even more challenging to uncover.

IV. Detection of Algorithmic Pricing

Detection of algorithmic collusion is a two-step process. Firms do not necessarily announce they are using pricing algorithms, so the first step may be to identify their usage. This is important because while many of the traditional methods for cartel screening can be adapted for algorithmic sellers, as will be discussed below, algorithmic sellers appear to display unique behavioral dynamics.

As noted above, there have been very few papers that examine the behavior of real-world pricing algorithmics. To the authors' knowledge there are only three main papers that do so.

The seminal paper by Chen et al. represents the first major attempt to detect algorithmic sellers, in this case on the Amazon Marketplace.[69] The authors operated with the assumption that algorithmic sellers would update their prices more frequently, and that their prices would be more strongly correlated to the prices of other sellers. After all, a seller seeking to offer the lowest price for a given product must be setting their price relative to the competitor with the current lowest price. As such they examined prices pegged to the lowest price, second lowest or that of the first party (*i.e.*, Amazon). The authors were unable to use the Amazon Marketplace Web Services API, as it was both heavily rate limited and did not return the identity of the third-party sellers, and so they resorted to web scraping.

This technique was subsequently adapted by Wieting and Sapi to analyse Bol.com, the largest online marketplace in the Netherlands and Belgium.[70] They decided that frequency of changes was the most reliable indicator of algorithmic pricing, with price correlation serving as a robustness check for two reasons. First, because the data they used only covered a small sample of a seller's product range, meaning that a high number of observed prices likely implied orders of magnitude more changes across the entire product portfolio. Doing this would be impractical without automated

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[68] Maarten Pieter Schinkel, *Balancing Proactive and Reactive Cartel Detection Tools: Some Observations*, OECD POLICY ROUNDTABLES: EX OFFICIO CARTEL INVESTIGATIONS AND THE USE OF SCREENS TO DETECT CARTELS 263 (2013), https://www.oecd.org/daf/competition/exofficio-cartel-investigation-2013.pdf.

[69] Chen et al., *supra* note 2.

[70] Marcel Wieting & Geza Sapi, *Algorithms in the Marketplace: An Empirical Analysis of Automated Pricing in E-Commerce* (NET Institute Working Papers 21-06, 2021), https://papers.ssrn.com/abstract=3945137.

repricing tools. Second, correlations with other prices may simply fail to detect algorithms not reliant on a price-correlation strategy and cannot be relied upon at all in monopoly markets.

Finally, Assad et al. were able to use a Quandt-Likelyhood Ratio test, which tests for a structural break for each period in some interval of time,[71] to estimate if and when German gasoline retailers adopted algorithmic pricing, based on the fact that trade publications reported mass adoption occurred beginning in 2017.[72] They did this by testing for structural breaks at each station for each week in a large window around the time of supposed adoption, relying on the number of daily price changes, the average size of price changes and the response time of a station's price update given a rival's price change. As with Chen et al., the authors assume that the adoption of algorithmic pricing will correspond to more frequent updates and faster reaction to competitor behavior.

From this, it appears that there is little difficulty in detecting the use of algorithmic pricing. The main obstacle, as discussed below in section VI, is the sheer volume of data that algorithmic pricing systems generate and that must be studied if their behavior is to be quantified.

V. Cartel Screens

Once algorithmic pricing has been identified, it is a matter of quantifying the algorithms' behavior and flagging up any activity that could indicate collusion or other harmful practices. These indications will not definitively demonstrate wrongdoing, which requires an agreement to fix trading conditions, but can serve as a trigger for a more detailed investigation by regulators.

Based on the limited research available and previous studies of cartel behavior, it appears possible to identify patterns that indicate supra-competitive prices consistent with collusive behavior. These patterns include:

- Low price variance, which can occur when it is costly or difficult to coordinate price changes[73] or when buyers start to become suspicious of the presence of a cartel following a period of price rises.[74]

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[71] *See* Richard E Quandt, *Tests of the Hypothesis that a Linear Regression System Obeys Two Separate Regimes*, 55 J. AM. STATISTICAL ASS'N 324 (1960).

[72] Assad et al., *supra* note 61.

[73] Rosa M. Abrantes-Metz et al., *A Variance Screen for Collusion*, 24 INT'L J. IND. ORG. 467 (2006).

[74] Joseph E. Harrington & Joe Chen, *Cartel Pricing Dynamics with Cost Variability and Endogenous Buyer Detection*, 24 INT'L J. IND. ORG 1185 (2006).

- Increased price uniformity across firms and the reduction in discounts, to simplify the functioning and monitoring of the cartel agreement.[75]
- A negative correlation between price and demand. During periods of high demand, the pay-off for cartel numbers defecting and undercutting the cartel price is higher, so the cartel is only stable with lower prices.[76]
- Sharp increases in high price-cost margins. High-cost margins alone are evidence of market power, and do not imply collusion, but sharp increases (absent any exogenous factors like a spike in demand) may be difficult to explain without the existence of a cartel.[77]
- Prices going up quickly and remaining high for a relevant period, with temporary sudden drops followed by prices going up again to previous levels, suggests collusion with periods of cheating followed by successful punishment and re-establishing of collusion. This can occur when a collusive agreement breaks down (for example, because of a new entrant) and is then restored.[78]
- A sharp and steady price increase following a steep decline. This can be attributed to the formation of a cartel in reaction to an event that caused a sharp decline in prices.[79]

In relation to all the above patterns, it is important to control for exogenous factors that can explain the behavior in ways other than collusion, such as variations in cost, in demand, or in external factors such as regulation or taxation, geopolitical shocks, or changes in trade or customs rules.

For human relatable conduct, it can be expected that many previously identified indicators would still be relevant, but the indicators may be altered to be harder to detect. For example, as alluded to previously, algorithms may allow firms to distinguish more accurately between periods where demand is low and when a cartel partner is cheating. This could improve cartel stability, and therefore reduce instances of the sharp decline and price restoration pattern associated with a breakdown of the cartel and subsequent punishment periods. However, modelling by Miklós-Thal and Tucker suggests that better predictive power may undermine cartel stability by increasing the temptation to undercut prices during periods of high

[75] OECD, *Ex officio cartel investigations and the use of screens to detect cartels*, OECD Competition Policy Roundtable – Crisis Cartels 29 (2011), https://www.oecd.org/daf/competition/cartels/48948847.pdf
[76] J. E. Harrington, *Detecting Cartels*, HANDBOOK OF ANTITRUST ECONOMICS, 26-29 (2008).
[77] *Id.* at 20-22.
[78] Edward J. Green & Robert H. Porter, *Noncooperative Collusion under Imperfect Price Information*, 52 ECONOMETRICA: J. ECONOMETRIC SOC'Y 87 (1984).
[79] OECD, *supra* note 75, at 55.

demand.[80] O'Conner and Wilson reach similar conclusions and show that cartels may need to resort to longer punishment periods and sub-monopoly pricing to maintain stable collusion.[81] These may require adjusting or reformulating screening patterns accordingly.

A further complication is that algorithms may reliably implement more sophisticated cartel arrangements. For example, the Autorité de la Concurrence and Bundeskartellamt propose that algorithms could even be used to attempt to deliberately conceal cartel behaviour by being programmed to implement different prices during periods of low demand or being set to occasionally generate periods of price heterogeneity or instability.[82] If this were true, we might see less of a trend towards price homogeneity, and as such, that indicator may cease being an effective screen.

To date, however, there has been relatively little empirical or modelling work on the potential impact of algorithms.[83] More generally, there has also been relatively little examination or modelling of the pricing patterns associated with algorithmic pricing systems and, in particular, which of these patterns might signify unlawful collusive behavior.

Wieting and Sapi identified five price patterns that were associated with repricing software but could not definitively ascertain whether any of the five patterns could be attributed to collusive behavior:[84]

1. Jitters: rapid transitory increases or decreases in price
2. Rockets and feathers: pricing shooting up rapidly and then gradually decreasing, often reaching the starting point
3. Balloons and rocks: price increases slowly up to a point, then falls rapidly often to the starting point
4. Alternating prices: pricing jumps up or down for longer but transitory periods between two values.
5. Random jumps: pricing changes frequently in a seemingly random manner

[80] Jeanine Miklós-Thal & Catherine Tucker, *Collusion by Algorithm: Does Better Demand Prediction Facilitate Coordination between Sellers?*, 65 MGMT. SCIENCE 1455 (2019).
[81] Jason O'Connor & Nathan E. Wilson, *Reduced Demand Uncertainty and the Sustainability of Collusion: How AI Could Affect Competition*, 54 INFO. ECON. & POL'Y 100882 (2021).
[82] Autorité de la Concurrence & Bundeskartellamt, *supra* note 45, at 28.
[83] *See* Assad et al., *supra* note 61.
[84] Wieting & Sapi, *supra* note 70, at Sec. 5.3.

Price jitters were also documented by Chen et al. but the jitters were attributed to malfunctions—"Transitory inconsistencies in Amazon's infrastructure, rather than actual price changes by sellers."[85] However, Wieting and Sapi found this explanation unconvincing and attribute the price jitters to actual pricing behavior for several reasons, the most critical being that there are products where the jitters led to a reaction by other actors, such as a change in the Buy Box seller.[86] The authors speculate that these jitters may be acting as a form of signaling, with a downward jitter indicating a firm's ability to reduce prices and punish deviating rivals. Downward jitters, where prices drop very briefly before returning to the previous baseline, are particularly concerning as they suggest that the firms in question are selling substantially above-cost most of the time. However, upward jitters could also signal to competitors an intention to raise prices, as Byrne and Roos documented for the Australian petrol market.[87] Further work would be needed to determine whether these patterns are harmless noise or intentional conduct consistent with cartel-like behavior.

Rockets and feather patterning was observed by Wieting and Sapi 11% of the time, and both are consistent with the classic collusion patterns described above, as well as the pricing patterns seen by Calvano et al.[88] and Klein.[89] In the absence of an innocent explanation such as unexpected cost shocks (unlikely to change within the timeframe examined), the authors suggest rockets and feather patterning are most likely due to algorithmic collusion, be it tacit or otherwise.

A rockets and feathers-type pattern was also identified by Musolff and was attributed to vendors adopting repricing software designed to undercut competitors in an attempt to win the Buy Box. The software is programmed to reset prices when they get too low or at a specific time of day, typically at night when sales are lowest.[90] The net result is pricing cycles reminiscent of Edgeworth price cycles, first proposed by Maskin and Tirole, but not driven by the same Markov perfect equilibria behavior (optimum pricing strategies that depend only on the current state of the system). Edgeworth cycles are a form of tacit collusion characterized by a slow decline in prices

[85] Chen et al., *supra* note 2, at 4.
[86] Wieting & Sapi, *supra* note 70, at 20.
[87] David P Byrne & Nicolas De Roos, *Learning to Coordinate: A Study in Retail Gasoline*, 109 AM. ECON. REV. 591 (2019).
[88] Emilio Calvano, et al., *Algorithmic Collusion with Imperfect Monitoring*, 79 INT'L J. IND. ORG. 102712 (2021).
[89] Klein, *supra* note 60; Wieting & Sapi, *supra* note 70.
[90] Leon Musolff, *Algorithmic Pricing Facilitates Tacit Collusion: Evidence from E-Commerce,* EC '22: Proceedings of the 23rd ACM Conference on Economics and Computation (2022), https://dl.acm.org/doi/abs/10.1145/3490486.3538239.

as firms take turns undercutting each other until both firms reach marginal cost.[91] At this point, the firms then enter a “war of attrition,” each waiting and hoping a competitor will raise prices first. When one firm eventually relents, the others will then raise their prices to slightly undercut this new higher price, and the cycle repeats.[92] According to Maskin and Tirole, once prices have dropped far enough, competitors switch from undercutting prices to pricing at marginal cost, and then randomize between resetting prices or keeping them unchanged in the hope that their rival might be the one to reset.[93] In the observed behavior, the minimum price is typically higher than the marginal price, and resetting occurs more frequently and deterministically, either once a pre-set level is reached (with no war of attrition) or at a set time (such as resetting every night during hours when sale probabilities are lowest regardless of whether the minimum was reached).[94]

The little empirical and economic research carried out so far suggests that, while previous models of cartel behavior are unlikely to become totally obsolete and our current understanding of cartelized markets will remain important in guiding further research, understanding how “collusion” works in the world of algorithms is still at its infancy. The next stage is, therefore, wide-spread and systematic analysis of markets affected by algorithmic pricing.

VI. Analyzing Algorithmic Pricing: Automation and the Data Problem

In this section we review issues that regulators face when dealing data generated with algorithmic systems. The sheer volume of price changes and pricing data generated by algorithmic pricing software makes it impractical to audit without relying on automated systems. In 2013, it was reported that Amazon implemented more than 2.5 million price changes per day, fifty times more than Best Buy and Walmart during the same period.[95]

In analyzing Bol.com, Wieting and Sapi performed two crawls. The first covered 2,840 products over a 30-day period and recorded 2,437,557 price changes, an average of 28 changes per product per day.[96] However, on average, crawl frequency

[91] Eric Maskin & Jean Tirole, *A Theory of Dynamic Oligopoly, II: Price Competition, Kinked Demand Curves, and Edgeworth Cycles*, 56 ECONOMETRICA: J. ECONOMETRIC SOC’Y 571 (1988).
[92] *Id.*
[93] *Id.*
[94] Musolff, *supra* note 90, at 24-25.
[95] Profitero, *Profitero Price Intelligence: Amazon Makes more than 2.5 million Daily Price Changes* (2013), https://www.profitero.com/blog/2013/12/profitero-reveals-that-amazon-com-makes-more-than-2-5-million-price-changes-every-day.
[96] Wieting & Sapi, *supra* note 70, at 12.

was only once every two hours.[97] The second covered 1,949 products over a different 30-day period and recorded 17,066,561 changes, an average of 292 changes per product per day with a crawl frequency of approximately 30 minutes.[98] Musolff relied on a near complete set of notifications for a single third-party repricing company which recorded 1,331,657,526 changes over a 577-day period, covering 859,823 products with three changes per product per day.[99]

Because of this volume of data, antitrust authorities are turning to technological tools to address the demands of digital markets.[100] However, there many legal and technical issues that must be overcome regarding the reliability of these tools as evidence and the ability for regulators to share data amongst themselves needed to build reliable tools.

The CMA has been an early adopter with the creation of the Data, Technology and Analytics (DaTA) unit in February 2019.[101] Other authorities such as the US Federal Trade Commission, and EU Directorate General for Competition have followed suit.[102] A notable success by the DaTA Unit is the in-house development of a tool to detect retail price maintenance (RPM) schemes by identifying anomalous patterns in scraped price data. The idea for the tool arose after an investigation in the musical instruments sector, where the CMA found that firms were using price monitoring software to determine compliance with RPM schemes.[103] The CMA intends to use this tool to monitor other sectors for suspicious pricing activity.[104]

A handful of other antitrust agencies have made similar tools.[105] The Columbian Superintendence of Industry and Commerce's "Sabueso" Project uses automated bots to monitor and analyze information about available goods on online retailers. Bots designed to simulate customers harvest product data. This is then supported by

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[97] *Id.*
[98] *Id.*
[99] Musolff, *supra* note 90, at 6.
[100] *See* Thibault Schrepel & Teodora Groza, *The Adoption of Computational Antitrust by Agencies: 2021 report* 2 STAN. COMPUTATIONAL ANTITRUST 78 (2022); Schrepel & Groza, *supra* note 64.
[101] Steven Hunt, *The Technology-Led Transformation of Competition and Consumer Agencies: The Competition and Markets Authority's Experience*, COMPETITION & MKTS. AUT. (2022), https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1085931/The_technology_led_transformation_of_competition_and_consumer_agencies.pdf.
[102] Competition and Markets Authority, *Compendium of Approaches to Improving Competition in Digital Markets* (2021), https://www.gov.uk/government/publications/compendium-of-approaches-to-improving-competition-in-digital-markets.
[103] Simon Nicols, *Restricting Resale Prices: How We're Using Data to Protect Customers*, COMPETITION & MKTS. AUT. (2020), https://competitionandmarkets.blog.gov.uk/2020/06/29/restricting-resale-prices-how-were-using-data-to-protect-customers/.
[104] *Id.*
[105] For a comprehensive overview, *see* Schrepel & Groza, *supra* note 64.

machine learning systems used to identify identical products across different stores, as different retailers use dissimilar names and descriptions.[106]

The Greek Data Analysis and Economic Intelligence Platform (DAECI) collects data from e-katanalotis (Market Observatory) for the prices of foods and common household goods, OKAA (Central Markets and Fisheries Organization) and Eurostat for the price of fruit, vegetables, meats, and fish, and fuelprices.gr for fuel prices.[107] In 2023 it started collecting product data from online retailers directly, with daily updates for over 60,000 products.[108] Similarly, the Armenian Competition Protection Authority has created an "e-Compete" platform designed to collect daily prices of selected goods via the State Revenue Committee databases.[109] While this will no doubt help detect instances of price fixing, daily snapshots will likely be unable to capture algorithmic pricing dynamics and, depending on when the snapshot is taken, could miss elevated pricing behavior. Equally, however, more frequent updates would require significantly more resources and data storage capabilities.

To reliably identify collusion in a given market with supervised learning, the AI must be trained on a dataset from the same market containing labelled instances of collusive and competitive behavior.[110] Datasets from other markets can be used, but the effectiveness of transposed models depends heavily on the comparability between markets.[111] If a sufficient volume of suitable data is unavailable, then training will be flawed, and the screen will likely be unreliable.[112] The same problem arises with unsupervised learning, where the dataset is unlabeled and the AI seeks to identify outliers that are most dissimilar from the "norm,"[113] as outliers can only be identified when there is sufficient data to establish a baseline.

Problems can arise even when an appropriate level of data is available. In 2017, the CMA released the "Screening for Cartels" (SfC) tool, designed to flag instances of potential bid-rigging.[114] The tool was made available to be freely disseminated and

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[106] Superintendence of Industry and Commerce, *Digital Evidence Gathering in Cartel Investigations – Note from Columbia*, (OECD, Latin American and Caribbean Competition Forum, 2020), https://one.oecd.org/document/DAF/COMP/LACF(2020)8/en/pdf.
[107] Schrepel & Groza, *supra* note 64, at 97.
[108] Schrepel & Groza, supra note 64, at 99.
[109] Schrepel & Groza, *supra* note 64, at 60.
[110] Rosa M Abrantes-Metz & Albert Metz, *Can Machine Learning Aide in Cartel Detection?*, ANTITRUST CHRONICLE, COMPETITION POL'Y INT'L (2018).
[111] Joseph E Harrington & David Imhof, *Cartel Screening and Machine Learning*, 2 STAN. COMPUTATIONAL ANTITRUST 134 (2022).
[112] *Id.*
[113] Ai Deng, *Cartel Detection and Monitoring: A Look Forward*, 5 J. ANTITRUST ENFORCEMENT 488 (2017).
[114] Albert Sanchez-Graells, '*Screening for Cartels' in Public Procurement: Cheating at Solitaire to Sell Fool's Gold?*, 10 J. EUR. COMPETITION L. & PRACTICE 199 (2019).

replicated for procurers in the UK and other jurisdictions. The tool, as released, was based on data from over 100 tenders, involving nearly 500 bids. However, there is no reliable centralized repository of procurement data. While individual regulators who decided to adopt the tool could train on further data, to this date any subsequent improvements could not be shared with others. Each parallel version would evolve in a different way. This is, of course, assuming the screens even evolved at all. In all likelihood, in the absence of a centralized repository, any single operator would be unlikely to provide enough data and carry out analyses over a sufficient number of tenders so as to meaningfully refine the system. Consequently, the CMA withdrew the SfC from use on January 20th, 2020.

The Danish Competition and Consumer Authority (DCCA) developed Bid Viewer, also designed to detect bid rigging and unusual patterns in public procurement. This tool was developed in collaboration with the Spanish and Swedish and other national authorities. These collaborators can share code, data and methodologies. However, there is still no single data source with procurement data available and the DCCA sees data acquisition as the largest obstacle.[115]

Such repositories can and should be created. The CMA DaTA team has created LEDA (which stands for "LEDA is an Environment for Data Analysis") a platform for creating what is known as a data lake—a centralized system for storing and accessing large quantities of raw data. This required developing the infrastructure necessary to ingest, curate and process sensitive data at scale, and acquired over 160 Terabytes of data across over 130 million objects at minimal cost between 2019 and 2022.[116] Following the DCCA's initiative with Bid Viewer, the authors suggest that greater international collaboration is necessary, particularly as national competition authorities seek to deal with global digital firms who operate in borderless markets. The challenges national competition authorities face are very similar and international collaboration can help alleviate the difficulties of acquiring in-house technical expertise and share the cost of developing new technologies.[117] Furthermore, international cooperation may allow for more and better data sets to be collected and pooled from different jurisdictions. International organizations such as the Organisation for Economic Cooperation and Development (OECD) or international cooperation networks such as the International Competition Network (ICN) could play a vital role of coordination on technology transfer and data sharing relevant to algorithmic pricing analysis. The OECD's Competition Committee has held best practice roundtables on Algorithms in 2017 and 2023 and developed

[115] Danish Competition and Consumer Authority, Data Screening Tools for Competition Investigations – Note by Denmark (OECD, 136th OECD Working Party 3 meeting 2022).
[116] Hunt, *supra* note 101 at 24.
[117] Hunt, *supra* note 101 at 45-46.

Council Recommendations on enhancing agency cooperation.[118] The ICN has recently created of the role of ICN Vice Chair Digital Coordination[119] and the Technologist Group, designed to act as a forum for discussion and knowledge sharing among agency technologists, data scientists and other digital experts.

The Hellenic Competition Commission argues that competition authorities should share cartel data from existing screens to create a training dataset for machine learning.[120] The CMA also notes that code sharing, including data pipeline, scraping, tools and analysis, could be a game changer for regulators and the benefits of international cooperation in these areas have the potential to be much higher than other forms of knowledge sharing among regulators.[121] In the area of bid rigging the Australian Competition and Consumer Commission has been internally advocating for more centralized, detailed and standardized collection of procurement data within Australia and believes there would be benefits to standardization of such data collection on a global scale.[122] This should apply equally to the development of standardization of data collection and formatting to facilitate the development and training of algorithmic screens in other market areas.

However, pooling national datasets is not necessarily straightforward. Huber, Imhof and Ishii studied the transferability of national screening datasets using Swiss and Japanese datasets.[123] Seven different models were used, relying on screens based on the variance, asymmetry and uniformity of bids. Two models relied on all the screens, but with one also including the number of bids and contract values; another two relied on all the screens but subject to demeaning (centering the screens within countries such that they have a zero mean), while the remaining three each relied on just two categories of screens.

Models trained and tested on just the Japanese dataset had a detection rate of 93 to 97% However, models trained on one national dataset and tested on the other proved less effective. Ensemble models (which rely on the weighted average of six

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[118] Competition & Mkts. Aut., *Compendium of Approaches to Improving Competition in Digital Markets*, 47-48 (2023), https://www.gov.uk/government/publications/2023-compendium-of-approaches-to-improving-competition-in-digital-markets.

[119] Australian Competition & Consumer Comm'n, *ACCC Chair Rod Sims appointed to International Competition Network Role* (2021), https://www.accc.gov.au/media-release/accc-chair-rod-sims-appointed-to-international-competition-network-role.

[120] Hellenic Competition Comm'n, *Computational competition law and economics - an inception report* (2021), https://www.epant.gr/en/enimerosi/publications/research-publications/item/1414-computational-competition-law-and-economics-inception-report.html.

[121] Hunt *supra* note 101, at 45-46.

[122] Australian Competition and Consumer Comm'n, *Data Screening Tools for Competition Investigations* (OECD, 136th OECD Working Party 3 meeting 2022).

[123] Martin Huber et al., *Transnational Machine Learning with Screens for Flagging Bid-Rigging Cartels*, 185 J. ROYAL STAT. SOC'Y SERIES A: STATISTICS IN SOC'Y 1074 (2022).

different algorithms: bagged decision trees, Bayesian additive regression trees, random forest, lasso regression, support vector machines and neural nets) had an overall detection rate of 82% to 88%. However, these models had a significance imbalance, as much as 20%, in the detection rate for competitive tenders and collusive tenders. Models based on just random forest were significantly less effective across the board with overall detection rates dropping to between 58% and 62%.

This performance drop was attributed to differing institutional dynamics in the tendering process across the two countries. For example, the coefficient of variance in collusive Swiss tenders is generally higher than in collusive Japanese tenders, likely due to additional cost estimate information available to Japanese firms. This means that the bid pattern for competitive Japanese tenders is comparable to that of collusive Swiss tenders.

However certain specific subsets of predictors, such as bid asymmetry, seemed robust to differing national dynamics. Relative comparators were also quite effective. While in absolute terms all Japanese tenders had less variance than Swiss tenders, collusive bids in both countries still have lower variance compared to the national baseline. By applying the process of demeaning, to reduce the institutional differences across countries, the authors were able to obtain detection rate of between 85% and 90% for the ensemble models. This strongly suggests that international, multilateral cooperation, whilst not without challenges, is likely to be the way forward.

In 2019, a survey of OECD and ICN members reported that many do not have any legal restrictions on sharing authority confidential information (information held by an authority that is not in the public domain and while not prohibited by statute from sharing, is considered confidential or sensitive) between regulators and that doing so would be valuable. All the respondents reported that there is no difficulty with sharing publicly available information.[124]

One potential solution would be to rely on synthetic data to avoid privacy concerns.[125] This involves the creation of artificial datasets derived from the original that reproduces its structure and characteristics. Ideally this provides training data and allows for valid statistical inferences to be made, without needing to disclose sensitive or confidential information. This typically relies on altering the data, such as by swapping the values of a few variables, adding random minor perturbations, or

[124] OECD/ICN, Report on International Co-operation in Competition Enforcement 176 (2021).
[125] Eur. Data Protection Supervisor, *Synthetic Data* (2022), https://edps.europa.eu/press-publications/publications/techsonar/synthetic-data_en.

coarsening the variables by using larger categories (such as grouping by county or state rather than zip code).[126] These techniques are already widely used in healthcare to avoid revealing data about individual patients.[127]

However, this field is relatively new and there are many technical obstacles to overcome. There is no standard measure for the utility of synthetic data,[128] and the strategies for how best to generate synthetic data for use in machine learning (and how best to tune models) is still an area of active research.[129]

Synthetic data can be created without direct use of collected data using a data simulator. This has the potential to reduce training costs, as data collection and processing tends to be complex and labor intensive. [130] Unfortunately, these simulators can only generate data based on an existing model, and so the quality of the generated data depends on how well the underlying phenomenon is understood and at the moment the empirical dynamics of pricing algorithms is poorly understood.

VII. Analyzing Algorithmic Pricing: Empirical and Technical Audits

Having discussed the issues of collecting data, in this section we review how pricing algorithms can be analyzed. In order to understand whether algorithmic pricing leads to collusive outcomes, it is first of all necessary to develop adequate tools to verify how the algorithms behave on the market. We discuss here the tools available and whether competition authorities are already equipped to use them or should be given new powers to this end.

Broadly speaking there are two main kinds of audits. Empirical audits attempt to measure the effect of an algorithm by observing inputs and outputs,[131] while a technical audit examines the underling code or data.

[126] Trivellore E. Raghunathan, *Synthetic Data*, 8 ANN. REV. STATISTICS AND ITS APPLICATION 129 (2021).
[127] *See* Synthetic Data, CPRD https://www.cprd.com/content/synthetic-data.
[128] Joshua Snoke et al., *General and Specific Utility Measures for Synthetic Data*, 181 J. ROYAL STAT. SOC'Y SERIES A: STATISTICS IN SOC'Y 663 (2018).
[129] Fida K Dankar & Mahmoud Ibrahim, *Fake It Till You Make It: Guidelines for Effective Synthetic Data Generation*, 11 APPLIED SCIENCES 2158 (2021).
[130] Michal Gal & Orla Lynskey, *Synthetic Data: Legal Implications of the Data-Generation Revolution* 109 IOWA L. REV. (forthcoming).
[131] Competition & Mkts. Aut., *Auditing Algorithms: The Existing Landscape, Role of Regulators and Future Outlook* (2022), https://www.gov.uk/government/publications/findings-from-the-drcf-algorithmic-processing-workstream-spring-2022/auditing-algorithms-the-existing-landscape-role-of-regulators-and-future-outlook.

As discussed above, there is relatively little empirical research on the pricing patterns caused by algorithmic systems, and even fewer on algorithmic driven collusion.[132] However, trying to investigate harm caused by algorithms does have one potential major advantage. For an algorithm, there is no difference between simulated test data and actual market data. Given identical inputs, an algorithm should respond in identical ways. Therefore, it is, in principle, easier to model the behavior of an algorithm more accurately without the need for simplifying assumptions and approximations for how it will act in a given situation.

An empirical audit was used in the European Commission's investigation of Google's search engine, where it was found that it was giving preferential treatment to its own comparison-shopping service, promoting it in search results at the expense of competitors.[133] Google had implemented the "Panda" algorithm , which they claim was designed to reduce the rankings of sites with low quality content and promote sites with unique, informative and original content. The Commission was able to show that this algorithm downranked competing comparison-shopping services, while Google's own Shopping service was exempted.[134] Critically, as part of their evidence, the Commission was able to simulate the effect of swapping the order of generic search results search queries to demonstrate that the same search result received more traffic when higher rated, demonstrating that Google's downranking harmed competitors. This result may seem intuitive but proving it was an essential part of the case. The Commission's empirical analysis involved using 5.2 Terabytes of search results, the equivalent of 1.7 billion queries.

While this does include analysis of historical data on inputs, it also includes testing the algorithm by submitting specific simulated queries. This can be done on the live system. For example, Chen et al. were able to analyze how Uber's surge pricing algorithm worked by emulating 43 copies of the Uber smartphone app over a period of four weeks.[135] Alternatively, this exercise can be performed in a "sandbox", running an isolated copy of the algorithm in a controlled environment. This avoids the risk that the algorithm might learn from the test input data, for example, repeated searches for a specific product might be interpreted as increased interest, leading the pricing algorithm to raise prices. Sandboxing also potentially allows for the temporary freezing of some of the algorithm's parameters, allowing for a higher

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[132] *See* Wieting & Sapi, *supra* note 70; Assad et al., *supra* note 61.

[133] *See* Comm'n Decision AT.39740, Google Search (Shopping) (2017).

[134] Eur. Comm'n, *Statement by Commissioner Vestager on Commission Decision to Fine Google €2.42 Billion for Abusing Dominance as Search Engine by Giving Illegal Advantage to Own Comparison Shopping Service* (2017), https://ec.europa.eu/commission/presscorner/detail/en/STATEMENT_17_1806.

[135] Le Chen et al., *Peeking Beneath the Hood of Uber* (Proceedings of the 2015 internet measurement conference, 495-508, 2015), https://dl.acm.org/doi/10.1145/2815675.2815681.

degree of control at the cost of the algorithm demonstrating non-realistic behavior due to the artificial setting.[136]

One of the main limitations of the empirical audit technique is that while it can identify potentially problematic behavior, it will not typically reveal the *cause* of the behavior in the algorithmic code or how to address it. In order to do so, it is possible to go one stage further and conduct a technical audit.[137] With a technical audit not only can an algorithm's behavior be accurately tested, but it is possible to "read its mind" by analyzing the underlying code. While regulators can only infer the reasoning and decision-making processes of human actors, the decisional parameters of an algorithm can be determined precisely.[138] Attempts to obfuscate collusive conduct by generating periods of apparent price instability as discussed above could hinder detection attempts, but the code of the system would reveal those efforts through a technical audit.

Technical audits do have their downsides, however, as direct code analysis is not necessarily straightforward.[139] The source code can be extensive, complex, or lacking in documentation. Algorithms based on machine learning tend to be "black boxes," where the decision-making processes and the precise relevance of input parameters can be opaque. These systems can be more readily understood through an empirical audit.[140]

Harrington suggested that certain algorithmic features or decision rules may be more liable to lead to anti-competitive outcomes and therefore proposed a research program in which learning algorithms could be tested in a simulated market under a range of conditions.[141] By examining when and under what circumstances supracompetitive or competitive prices emerge, it may be possible to identify what properties are present for supracompetitive prices but not competitive prices.[142] This could ease the burden associated with technical audits, as it may be possible to establish certain classes of algorithms that could either be prohibited or presumed to be anticompetitive if they have no plausible rationale other than to facilitate an anti-competitive outcome.[143] A full technical audit would only be required if none of these features are present. There is some evidence to suggest that asynchronous learning

[136] Autorité de la Concurrence & Bundeskartellamt, *supra* note 45, at 72.
[137] Competition & Mkts. Aut., *supra* note 102.
[138] Michal Gal, *Algorithms as Illegal Agreements*, 34 BERKELEY TECH. L. J. 68 (2019).
[139] *See* Autorité de la Concurrence & Bundeskartellamt, *supra* note 45, at 70.
[140] *Id.* at 71-73.
[141] Harrington, *supra* note *24*.
[142] *Id.*
[143] *Id.*

models, where the AI only learns about the result of the action it took, is more liable to lead to near monopoly pricing while synchronous learning, where the AI also learns the result of alternative actions it could have made, leads to competitive pricing.[144]

Regulators could be given new powers that could require companies to assist in testing algorithmic systems, both to assist in the development of more effective algorithmic screens, and to aid in follow up investigations once potentially problematic conduct has been detected. For example, the current Digital Markets, Competition and Consumers Bill will give the CMA new investigative powers in relation to the digital markets regime, including powers to require a person to obtain, generate, collect, or retain specified information or to conduct a specified demonstration or test.[145] This would give the CMA the power to require an undertaking to demonstrate how an algorithm operates or undertake empirical audits or sandbox testing of the algorithm and report the outcomes.

Tsoukalas has suggested that New Competition Tool (NCT) should be resurrected to address the threat of algorithmic collusion.[146] Currently the Commission has no remedial powers following a sector inquiry. The NCT was a proposal, seemingly modelled after the UK's market investigation system, to grant the Commission the power to impose structural or behavioral remedies following an investigation.[147] The NCT was abandoned following consultation, and not included in the Commission's proposal for the Digital markets Act.[148]

Under the Enterprise Act 2002 the CMA is granted the power to impose market wide remedies independent of any individual infringement proceedings.[149] The CMA may launch an investigation if it has reasonable grounds for suspecting that certain features of the market "prevents, restricts or distorts competition in connection with the supply or acquisition of any goods or services in the United Kingdom or a part of the United Kingdom."[150] If there is a finding of an "adverse effect on competition," the CMA has the power to take such action "as it considers to

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[144] John Asker et al., *The Impact of Artificial Intelligence Design on Pricing*, J. ECON. & MGM. STRATEGY (2023).

[145] Digital Markets, Competition and Consumers HC Bill (2022-23) § 350 §§ 68.

[146] Vasileios Tsoukalas, *Should the New Competition Tool be Put Back on the Table to Remedy Algorithmic Tacit Collusion? A Comparative Analysis of the Possibilities under the Current Framework and under the NCT, Drawing on the UK Experience*, 13 J. EUR. COMPETITION L. & PRACTICE 234 (2022).

[147] Eur. Comm'n, *New Competition Tool* (2020), https://ec.europa.eu/info/law/better-regulation/have-your-say/initiatives/12416-Single-Market-new-complementary-tool-to-strengthen-competition-enforcement_en.

[148] Eur. Comm'n, *Proposal for a regulation of the European Parliament and of the Council on contestable and fair markets in the digital sector (Digital Markets Act)* COM (2020) 842 final (Dec. 15, 2020).

[149] Enterprise Act 2002, s 138(2).

[150] *Id.* at s 131(1).

be reasonable and practicable to remedy, mitigate or prevent" it as well as resultant "detrimental effects on customers."[151] This flexible tool allows the CMA to address problems that might otherwise be difficult to remedy in a targeted and evidence-based way. In the context of algorithmic collusion, these powers would circumvent the question of whether autonomous algorithmic conduct amounts to an infringement and allow for prospective remedies designed to make the market less susceptive to this form of collusion in the future.[152]

One extreme option would be to outright ban algorithmic pricing under certain conditions. In August 2023 the Italian government adopted a legislative degree seeking to ban algorithmic pricing for domestic flights from Sicily or Sardinia when sold during peak-demand seasons and if the resultant ticket price was 200% higher than the average fare. It also sought to ban algorithmic personalised pricing based on profiling. Such heavy-handed measures would likely have likely disincentivise further investments in algorithmic systems, which, in general bring about significant efficiency gains. Indeed, following an intervention by the European Commission the Italian government has instead transferred the matter to Italian Competition Authority (ITA) to oversee, rather than imposing a ban.[153] Separately, the ITA launched a market inquiry into possible airline price fixing, but the investigation was closed on January 2024 without any finding of infringement.[154]

Another possibility, in light of the risks of automated conduct, would be to require sellers or third-party providers to test and train algorithms in a sandbox to ensure, as much as practically possible, that they are not prone to collusive outcomes. This may be analogous to the testing regime required for algorithmic trading on the financial markets within the EU. Art 17(1) of the Markets in Financial Instruments Directive II (MiFID II) requires algorithms to be tested in a simulated market to ensure that they do not behave in an unintended manner or "contribute to disorderly trading conditions" before they can be used on a trading venue.[155] Article 48(6) MiFID II further obligates all trading venue operators to require their participants to both carry out "appropriate testing of algorithms" and to provide "environments to facilitate such testing."[156]

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[151] *Id.* at s 138(2).
[152] Francisco Beneke & Mark-Oliver Mackenrodt, *Remedies for Algorithmic Tacit Collusion*, 9 J. ANTITRUST ENFORCEMENT 152 (2021).
[153] Angelo Amante & Keith Weir, *Italy's Government Dilutes Plan to Cap Airfares To Islands*, REUTERS (2024), https://www.reuters.com/business/aerospace-defense/italian-govt-asks-antitrust-body-control-air-fares-islands-2023-09-19/.
[154] Italian Competition Authority, ICA's Bulletin No. 1 of 2 January 2024.
[155] Community Delegated Regulation (EU) 2017/589 of July 19, 2016 on the Organisational Requirements of Investment Firms Engaged in Algorithmic Trading O.J. (L 87/417).
[156] *Id.*

This provision is quite flexible, and seeks to be principle-based, rather than prescriptive. Instead of explicitly setting out the testing regime and the exact measures to be taken, which would risk the regulations becoming obsolete as newer technologies and techniques are developed, it sets out high level guidelines and their stated intent. The trading venue is obligated to provide a testing environment, which may be carried out internally or by a third party.[157] This could be implemented for certain markets or online platforms if algorithmic collusion becomes a major concern.

For example, Abada and Lambin found that some instances of apparent "algorithmic collusion" by reinforcement learning algorithms in a simulated energy market were due to insufficient exploration of the parameter space. The algorithms would converge on a supra-oligopolistic price but under testing the authors found it would punish both pro-competitive and pro-collusive deviations from it. Abada and Lambin found this could be addressed with improvements to the training regime with the inclusion of a maverick firm designed to bid aggressively when the other players appeared to reach a collusive outcome but otherwise bid conservatively led to a reduction in collusive outcomes and a commensurate improvement in overall social welfare.[158] More research is needed, but this suggests that requiring the inclusion of this kind of maverick in the training environment could prevent collusive outcomes.

A tiered, risk-based approach, similar to that envisioned by the EU Artificial Intelligence Act would likely be in order.[159] This would require identifying which market sectors or categories of system are most likely to be at risk. It is already well documented that certain market features, such as homogenous products or high barriers to market entry make collusion more likely and are therefore most at risk.[160] Similarly, it would almost certainly be disproportionate to require extensive testing of every algorithmic pricing system. Instead, the regime should only be limited to algorithms with large user bases or companies with significant market power.

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[157] Patrick Raschner, *Algorithms Put to Test: Control of Algorithms in Securities Trading Through Mandatory Market Simulations?*, Eur. Banking Inst. Working Paper Series No. 87 (2021), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3807935.

[158] Ibrahim Abada & Xavier Lambin, *Artificial Intelligence: Can Seemingly Collusive Outcomes Be Avoided?*, 69 MGMT. SCIENCE 4973 (2023).

[159] Eur. Comm'n, *Proposal for a Regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) and amending certain Union legislative acts*, COM (2021) 206 final (Apr. 21, 2021).

[160] OECD, *supra* note 6, 20-22.

VIII. Conclusion

Digital markets are evolving rapidly and the use of pricing algorithms is becoming increasingly prevalent. While they provide many benefits, there is a real risk that they will bring new harms and new challenges for regulators seeking to prevent anti-competitive behavior.

This paper did not address the question of what types of algorithmic pricing are or may be antitrust violations. It also does not address the issue of whether tacit collusion, which is not generally considered a violation in the absence of direct or indirect human contact, should become a concern if achieved through the means of algorithmic pricing. In the authors' view, the first and most important step at this stage is to understand the functioning of markets affected by algorithmic pricing in order to verify whether the impact on the economy of new forms of "collusion" is sufficiently severe to warrant a rethink of the law or even the introduction of new regulatory tools.

To date, while preliminary evidence appears to suggest that pricing algorithms have an impact on observed patterns of pricing behavior, there has been comparatively little research into this area.[161] More research is needed, not just to detect what patterns can be attributed to collusive outcomes, but what regular unlawful algorithmic behavior looks like.

Going forward, the authors consider the following five action points to be of crucial importance in developing the knowledge that is needed for policy-making in this area:

1. While there have been many theoretical studies, more empirical and economic research is needed on the behavior and characteristics of actual implementations of algorithmic pricing. In the first place, this could be driven by competition authorities. To this end, competition authorities, possibly leveraging on the existing frameworks of the OECD or the ICN, should cooperate internationally to share technologies and pool data, so that effective algorithms can be developed and trained to review and analyze algorithmic prices.
2. Legal barriers to the sharing of technology and data internationally among competition authorities for this purpose should be removed, while retaining adequate safeguards if information is sensitive or confidential, or if third-

[161] *See* Wieting & Sapi, *supra* note 70.

party rights are otherwise affected. Consistent standards for the collection and formatting of data should also be developed.

3. Competition authorities should be given adequate investigative powers to run empirical and technical audits, including enhanced data gathering powers to this effect. This would be particularly important in relation to "deep learning" algorithms, which do not respond to any predefined set of rules.
4. Data and outcomes obtained by competition authorities, and, indeed, other public authorities, should be made available, with appropriate safeguards, to independent, academic researchers, whose work would prove crucial in complementing, expanding upon, and verifying any research carried out by competition authorities. Furthermore, public enforcers may not have the resources to exploit the full potential of the data they have or to follow all clues, which is instead the task of independent academia. This could be akin to the data access and scrutiny provisions Digital Services Act, which grants vetted researchers access to data from very large online platforms and very large online search engines for the purposes of research that contributes to the detection, identification and understanding of systemic risks.[162]
5. In the short term, in light of the risks of automated conduct, a possible solution would be to require sellers or third-party providers to test algorithms above a certain user threshold in a sandbox to ensure, as much as practically possible, that they are not prone to collusive outcomes. A solution for certain markets or online platforms analogous to the testing regime required for algorithmic trading on the financial markets could be implemented if algorithmic collusion were to become a major concern. [163]

[162] Regulation (EU) 2022/2065 of the European Parliament and of the Council of Oct. 19, 2022, on a Single Market for Digital Services and Amending Directive 2000/31/EC (Digital Services Act), O.J. (L 277), Art 40.
[163] Commission Delegated Regulation (EU) 2017/589 of July 19, 2016, Supplementing Directive 2014/65/EU of the European Parliament and of the Council with regard to Regulatory Technical Standards Specifying the Organisational Requirements of Investment Firms Engaged in Algorithmic Trading,O.J. (L 87), Art 17(1)(d).