CPI Columns
US & Canada

August 2025

Between Efficiency and Illegality: The Competitive Implications of Surveillance and Algorithmic Pricing

By: Sencer Ecer & Mehmet Ekmekci

Edited by Justin Stewart-Teitelbaum & Angela Landry

Between Efficiency and Illegality: The Competitive Implications of Surveillance and Algorithmic Pricing

By Sencer Ecer & Mehmet Ekmekci[1]

I. Emerging Enforcement Actions re: Surveillance and Algorithmic Pricing

On February 4, 2010, the DOJ filed a Statement of Interest opposing the Google Books Settlement, objecting to, among other things, the parties' joint delegation of pricing decisions to a shared algorithm, potentially constituting collusive behavior under antitrust law. This objection provided an early sign of the enforcement agencies' alertness to algorithmic pricing. Algorithmic pricing is defined as the practice where companies use computer programs, either directly or via third parties, to automatically set prices based on market data, competitor prices, and customer behavior. This practice may include dynamic pricing, where prices frequently change and adapt, and is based on advanced computer programming such as using machine learning or AI-powered software (MacKay et al., 2024).[2]

Surveillance pricing is a newer concept, in which a pricing regime is dependent on inputs derived from meticulously following consumers' every move and across every possible platform, e.g., mouse movements while shopping online, likes on social media, time spent viewing online content, etc. Although the concept of algorithmic pricing predates surveillance pricing, the contemporary pricing stack has inverted the hierarchy: surveillance practices now function as the upstream data infrastructure upon which algorithmic pricing increasingly depends. Thus, currently, surveillance pricing is functionally upstream of algorithmic pricing, shaping its scope and granularity.

Concerns over surveillance pricing have also been raised. The New York Senate is seeking transparency by trying to enact the "Preventing Algorithmic Pricing Discrimination Act."[3] Meanwhile, the FTC raised serious concerns on surveillance pricing practices, although its 6(b) study (2024) on surveillance pricing has not yet concluded.[4] The main goals of this study are to catalog the types of data sourced to "fuel" the companies' algorithms and where the data is sourced. Concerns include

[1] Senior Vice President, Compass Lexecon; Professor of Economics, Boston College and Senior Consultant, Compass Lexecon

[2] MacKay, A., Svartback, D., & Ekholm, A., Dynamic Pricing, Intertemporal Spillovers, and Efficiency," working paper (2024).

[3] The act will require "Any person who knowingly advertises, promotes, labels or publishes a statement, display, image, offer or announcement of personalized algorithmic pricing using consumer data specific to a particular individual shall include with such statement, display, image, offer or announcement a clear and conspicuous disclosure that states: "THIS PRICE WAS SET BY AN ALGORITHM USING YOUR PERSONAL DATA." New York State Senate. (2025). S7033: An act to amend the general business law, in relation to algorithmic pricing disclosure requirements. https://www.nysenate.gov/legislation/bills/2025/S7033

[4] Federal Trade Commission. (2024, July 1). Surveillance pricing: 6(b) study research summaries (Redacted Version) [Report No. P246202]. https://www.ftc.gov/system/files/ftc_gov/pdf/p246202_surveillancepricing6bstudy_researchsummaries_redacted.pdf

targeted pricing and user segmentation practices, where targeted pricing refers to determining prices, quantities, or availability based on consumer data and user segmentation refers to building individual consumer profiles. These concerns are closely related to algorithmic pricing concerns hence we do not separately discuss them. Another concern that emerged while conducting the study is the utilization of search and product ranking tools by companies. These tools essentially alter search costs for the market by altering the prominence of the alternatives presented to the consumer, which may have pro and anticompetitive effects, which we discuss at the end of Section V. In the remainder of this article, we refer to algorithmic pricing in a manner that already incorporates surveillance-driven inputs; distinctions between algorithmic and surveillance pricing are made where analytically relevant.

The first criminal case on algorithmic pricing came in 2015, U.S. v. David Topkins, where Mr. Topkins pleaded guilty to using automated pricing algorithms to coordinate prices for posters sold online, particularly in the Amazon Marketplace.[5] The case concluded with a criminal conviction, fueling growing interest in collusive and other anti-competitive conduct involving algorithmic pricing. This is reflected in numerous subsequent cases in the US, EU, and UK, including private litigation, some of which prompted Statements of Interest from the DOJ and FTC.[6] In all the US cases, the government or private parties have asserted claims of illegal price-fixing and restraint of trade in violation of the Sherman Act, Section 1. Thus, these cases are essentially motivated by higher observed prices, but higher prices can be the outcome of both lawful and unlawful activities. Our aim in this article is to shed light on the capabilities and possible outcomes of surveillance and algorithmic pricing practices considering the most recent economic research. There are different concepts of efficiency in economics. In this article we carefully treat different economic concepts of efficiency, which lie at the heart of the debates. The article clarifies the distinction between lawful strategies like price discrimination, and illegal collusion. It then reviews recent findings on algorithmic collusion, and concludes with our observations.

II. Cost Reductions Enabled by Algorithmic Pricing May Reduce Prices and Improve Productive Efficiency

We first discuss algorithmic pricing in the context of productive efficiency, the core concept when we discuss cost-reducing technologies or synergies. Productive

[5] United States Department of Justice. (2015, April 6). *U.S. v. David Topkins*.

[6] *U.S. v. Aston & Trod Ltd.* (2015); *Trod Ltd/GB Eye Ltd.* case in the UK: Online sales of posters and frames, Case 50223, Decision of the CMA, dated 12 August 2016; *In re RealPage, Inc.* Rental Software Antitrust Litigation (2022) in parallel with DOJ's case; *Duffy v. Yardi Systems, Inc.* (2023); *Gibson v. MGM Resorts International et al.* (2023); *In re MultiPlan Health Insurance Provider* Litigation (2024); Comisión Nacional de los Mercados y la Competencia (CNMC), Decision Booking S/0005/21 of 29 July 2024, S/0005/21 - BOOKING | CNMC; In re GoodRx and Pharmacy Benefit Manager Antitrust Litigation (No. II) (2025).

efficiency is achieved when a firm produces goods and services using the least resources possible and when output is maximized given existing resources and technology. Labor cost reductions from replacing manual pricing processes with automated algorithms significantly reduce the need for pricing analysts and manual price adjustments, especially for larger retailers such as Amazon and Walmart. Using real-time data may enhance demand forecasts, enabling better procurement and production planning, reducing waste and underutilization of capacity. In summary, algorithmic pricing can enhance productive efficiency through cost savings in pricing, inventory, and capacity management, and may have procompetitive effects. Next, we move to a more controversial effect of algorithmic pricing, what is, in practice, called "revenue" or "yield" management. Revenue management almost always entails a form of "price discrimination," which we discuss next.

III. Price Discrimination Enabled by Algorithmic Pricing May Improve Allocative Efficiency While Lawfully Raising Prices but with Notable Distributional Trade-Offs

Allocative efficiency is the condition in which trade is unrestrained, ensuring that resources are allocated to their highest-valued uses in the economy. Achieving allocative efficiency maximizes total surplus, which is the sum of consumer and producer surplus. Consumer surplus represents the gains of consumers from trade, and producer surplus represents the gains of producers from trade, more technically, their gross profits at fixed costs. Allocative efficiency is independent of the distribution of the total surplus between consumers and producers, which is critical in understanding the competitive impact of price discrimination.

In a typical market, some individuals are *willing (and able)* to pay higher amounts than others for the same product mainly due to their higher income or stricter preferences towards that product. Surveillance of consumers via price targeting or consumer segmentation and profiling tools allows firms to determine these relevant inputs and hence the consumer's willingness to pay (WTP) for a particular product or service at given locations, times, and sales channels. Price discrimination is the practice of charging different prices to different consumers or consumer groups based on their WTP. In perfect price discrimination ("PPD"), a seller charges each buyer their maximum WTP, capturing all of the consumer surplus. Thus, given a market structure and holding all other factors constant, if a firm engages in perfect price discrimination, then consumer surplus declines to zero, but this decline typically does not harm competition. Moreover, PPD improves allocative efficiency.

To see the mechanism that improves allocative efficiency while transferring consumer surplus to producers, note that surveillance and pricing algorithms enable perfect price discrimination based on location, device, browsing history, and behavioral cues (Nazzini & Henderson, 2024).[7] With surveillance pricing, estimating each consumer's WTP becomes more feasible. Once a consumer's WTP is known, firms aim to charge it via algorithmic pricing, provided it exceeds cost, as no more can be extracted in a voluntary exchange. Thus, with PPD, all surplus is now obtained by producers. Price discrimination may fail when secondary markets emerge or when competition leads to price undercutting. It works best with product differentiation, switching costs, price search costs, and no capacity constraints.

Consistent with the theory, Dubé & Misra (2023) show that average consumer surplus declines by 23 percent with algorithmic pricing, even though the consumers who join the market may still pay less than the previously prevailing uniform price.[8] Similarly, Marinova & Bergqvist (2025) warn that AI-driven price discrimination may harm consumers but argue that EU law is not yet well-suited to address it.[9] Somewhat paradoxically, however, allocative efficiency is achieved with PPD since there are no restraints to trade from output contraction. For these reasons the practice is generally not unlawful in the US or EU as long as it does not affect competition such as through exclusionary conduct. We next discuss the price increases caused by collusion facilitated by algorithmic pricing.

IV. Algorithmic Pricing May Facilitate Illegal Increases in Price

A. *Defining Explicit and Tacit Price Collusion*

A fundamental principle underpinning market economies is the preservation of competition as determined by laws. There are many ways firms can violate competition laws, including price collusion, sometimes referred to as forming cartels or price-fixing. We use "price collusion" to refer to explicit, generally illegal agreements between competitors to fix or manipulate prices.

Another concern is "tacit" collusion, which is also called "conscious parallelism." In tacit collusion, which is at this time mostly legal in the United States, firms coordinate their pricing behavior without explicit communication or a formal agreement (Massarotto, 2025).[10] Unlike explicit price collusion, tacit collusion arises through recognition of mutual interdependence. Just like in the case of lawfulness of monopoly versus unlawfulness of some monopolizing conduct, firms' awareness and utilization of their mutual interdependence is not illegal per se. An important exception exists when concerns about tacit collusion are legitimately addressed as a preventive measure in merger enforcement. The focus according

[7] Nazzini, R., & Henderson, J. (2024). *Overcoming the current knowledge gap of algorithmic "collusion" and the role of computational antitrust*. Stanford Computational Antitrust, Vol. IV. Stanford Law School.

[8] Dubé, J. P., & Misra, S. (2023). Personalized pricing and consumer welfare. *Journal of Political Economy*, *131*(1), 131-189.

[9] Marinova, D. M., & Bergqvist, C. (2024). Unlocking Manufacturer Utopia: AI's Role in Perfect Price Discrimination. *Available at SSRN 5153695*.

[10] Massarotto, G. (2025). Detecting Algorithmic Collusion. *Ohio State Law Journal, 2025*, *86*.

to the 2023 US Merger Guidelines is on the possibility of increased tacit coordination in coordinated effects analysis, "Because tacit coordination often cannot be addressed under Section 1 of the Sherman Act, the Agencies vigorously enforce Section 7 of the Clayton Act to prevent market structures conducive to such coordination."[11] Another exception in addressing tacit collusion may be emerging: Some suggested that tacit collusion via algorithmic pricing is qualitatively different from typical tacit collusion and as such should be treated as an explicit price collusion (Doerr, 2025).[12] Consistently, in February 2024, Senators Amy Klobuchar, Ron Wyden, Dick Durbin, Peter Welch, Mazie Hirono, and Richard Blumenthal introduced the Preventing Algorithmic Collusion Act, aiming to prohibit companies from using algorithms to collude on pricing, including tacit collusion (Macy et al., 2025). The EU Horizontal Cooperation Guidelines (2023) address algorithmic coordination directly albeit in a more general horizontal context.[13] Going forward, algorithmic pricing practices are likely to be under scrutiny, whether the concern is explicit or tacit price collusion or the potential to increase in their likelihood due to a merger. Economic theory focuses on the effects, not the form, of collusion, and thus does not strongly distinguish tacit from explicit price collusion in modeling competitive harm. We briefly review basic economic concepts next.

B. Price Collusion in the Chicago School Tradition

The well-known game Prisoners' Dilemma, where the criminals fail to cooperate, underpins the approach of the Chicago School of economic thought to price collusion, which argues price collusion is inherently fragile and unlikely to be sustained in competitive markets (Stigler, 1964).[14] The intuition is that deviation from collusion is of self-interest even though when everyone deviates, the outcome is worse for all. While Chicago School still dominates judicial doctrine, Post-Chicago insights increasingly inform enforcement strategy and policy design within regulatory agencies, so we discuss this school of thought next in relation to price collusion.

C. Price Collusion in the Post-Chicago School Position

The Post-Chicago School recognizes circumstances under which collusion may be sustainable (Friedman, 1971;[15] Abreu, 1986[16] & 1988[17]). A fundamental condition is that firms must expect to operate within the same market over an indefinite horizon,

[11] Federal Trade Commission & U.S. Department of Justice. (2023). *2023 merger guidelines*.

[12] Doerr, A. (2025). Algorithmic Tacit Collusion. In *An Analysis under European Competition Law* (pp. 1-368). Mohr Siebeck GmbH & Co. KG.

[13] Communication from the Commission, Guidelines on the applicability of Article 101 of the TFEU to horizontal co-operation agreements, OJ No C 259, 21.07.2023.

[14] Stigler, G. J. (1964). A theory of oligopoly. *Journal of Political Economy*, *72*(1), 44-61.

[15] Friedman, J. W. (1971). A non-cooperative equilibrium for supergames. *The Review of Economic Studies*, *38*(1), 1-12.

[16] Abreu, D. (1986). Extremal equilibria of oligopolistic supergames. *Journal of Economic Theory*, *39*(1), 191-225.

[17] Abreu, D. (1988). On the theory of infinitely repeated games with discounting. *Econometrica: Journal of the Econometric Society*, 383-396.

a dynamic typically modeled by infinitely repeated games rather than a one-shot interaction game as exemplified by the traditional Prisoners' Dilemma. Another necessary condition is that firms must sufficiently value future earnings relative to immediate profits, exhibiting a low rate of time preference or a high degree of patience. What then sustains collusion is the threat of some form of temporary or prolonged price war so long as deviations from collusion can be identified by the other firms. Thus, what makes price undercutting or extending the market to the competitor's market unprofitable is the threat that a full-blown price war will start if any of the firms fail to comply with the coordinated pricing plan.

The methodological shift to post-Chicago school was facilitated by Green & Porter (1984),[18] who show that elevated prices and profits consistent with collusion can be sustained in equilibrium without explicit communication, through strategies conditional on publicly observable but noisy market signals, that is, even when firms cannot perfectly observe each other's actions. This state constitutes a form of tacit collusion, where cooperation is self-enforcing despite imperfect monitoring. Thus, episodes of low prices may be part of a self-enforcing tacit collusion strategy, and not evidence of the failure of collusion. Thus, the post-Chicago school provides theoretical models that explain how market structures and strategic behavior can sustain both explicit and tacit price collusion. Now we move on to the discussion of price collusion under algorithmic pricing.

V. Algorithmic Pricing in the Shadow of Price Collusion Allegations

One of the central challenges in contemporary antitrust enforcement is identifying pricing algorithms that generate and sustain supracompetitive prices and assessing whether such algorithmic practices cross the line into illegality. There are two categories where the implementation of algorithmic pricing can be examined, collective and individualized use by firms, the former one also called the hub-and-spoke system.[19]

A. Hub and Spoke System

One use of algorithmic pricing is when a third-party offers an algorithm to many firms operating in an industry, the hub-and-spoke style. Surveys show that less than 30 percent of executives felt fully prepared to implement advanced algorithmic pricing and many rely on third-party tools or vendors. For this reason, hub-and-spoke systems are the priority concern (Spann et al., 2025).[20] Examples of such third-parties include RealPage, IDeaS, and Feedvisor. The

[18] Green, E. J., & Porter, R. H. (1984). Noncooperative collusion under imperfect price information. *Econometrica: Journal of the Econometric Society*, 87-100.

[19] For the remainder of this analysis, we set aside cases involving algorithms explicitly programmed to collude.

[20] Spann, M., Bertini, M., Koenigsberg, O., Zeithammer, R., Aparicio, D., Chen, Y., Fantini, F., Jin, G.Z., Morwitz, V., Leszczyc, P.P., Vitorino, M.A., Williams, G.Y. & Yoo, H. (2025). Algorithmic Pricing: Implications for Marketing Strategy and Regulation.

underlying algorithms collect information from all the users of the algorithm and hence have more precise information about the cost and demand shocks in the market. Then, the algorithm gives pricing suggestions to individual firms.

There are several concerns related to hub-and-spoke systems. First, without any explicit communication among the firms, the algorithm can facilitate tacit collusion (Spann et al., 2025). There is some evidence of tacit price coordination in airlines even though many still rely on pricing heuristics rather than dynamic AI models, so tacit collusion may be achieved more effectively with algorithmic pricing (Ge et al., 2025).[21] Indeed, Ge et al. (2025) use a difference-in-differences method and find that AI adoption correlates with a 2.5 percent average fare increase, with a 5.5 percent increase in low-end fares and reduced fare dispersion across routes. Second, even if the algorithm does not recommend prices above the competitive level, the aggregation of information substantially reduces pricing uncertainty; as a result, the algorithm's suggested prices — when uniform across firms — may facilitate tacit collusion. For example, a straightforward strategy for each individual firm to adopt is to use the suggested prices as a benchmark and charge 10 percent above the suggested price.[22] This strategy would be easy to adopt and implement, and deviations from this scheme are easy to detect since price suggestions are public.

In general, lack of transparency and the opacity of the algorithms are seen as subjects of regulation (Ebers & Gamito, 2021).[23] For example, if regulation requires transparency of the past recommendations of the software, a new entrant can undercut the prices. This is especially salient and effective if a new entrant also uses an algorithm that operates on undercutting competitors' prices by a rule-based percent. This could be a separate algorithm developed by the firm or a competing algorithm. If some firms are colluding, then a new algorithm can undercut opponents and facilitate entry, making initial collusion fragile. The regulators can also freely supply such algorithms. We next discuss markets where each firm is using its own algorithm, and the algorithms can potentially learn to collude.

B. Independent Usage

Sometimes pricing algorithms are used by firms independently, which can still lead to collusion. A frequently used type of an algorithm is Q-learning, which is a reinforcement learning algorithm that learns optimal actions by updating value estimates based on trial-and-error interactions to maximize long-term rewards. In a seminal paper, Calvano et al. (2020) showed via simulations that Q-learning algorithms can easily learn to collude without communication, just like

[21] Ge, Q., Kim, M., & Rupp, N. (2025, April 10). *Algorithmic collusion in the skies: The role of AI in shaping airline competition.* PYMNTS.

[22] Communication from the Commission, Guidelines on the applicability of Article 101 of the TFEU to horizontal co-operation agreements, OJ No C 259, 21.07.2023, p. 83.

[23] Ebers, M., & Gamito, M. C. (2021). *Algorithmic Governance and Governance of Algorithms*. New York: Springer.

human executives.[24] For example, the algorithms can use punishments for price cutting that lasts for a while, then gradually return to high prices, which is the "tit-for-tat" strategy effective in implementing tacit collusion. The tendency of algorithms to sustain supracompetitive prices remains robust even when more general reinforcement learning algorithms are employed (Faghani, 2025)[25] and in more general environments, like with cost uncertainty (Ballestero, 2025).[26] This kind of independent learning extends to other types of algorithms. Fish et al. (2024) show LLM models, which, unlike the reinforcement learning algorithms, are already trained with datasets, can also sustain collusive prices.[27] Their evidence suggests that the algorithms can avoid price undercutting to prevent price wars. More generally, Fish et al. (2024) confirm that these concerns are supported by theoretical studies, experiments, and empirical evidence. Thus, the possibility of collusive learning persists across diverse algorithmic types.

Yet, empirical evidence of supracompetitive prices is limited. For example, Assad et al. (2022)[28] present such evidence from the German retail gasoline market that in a duopoly where both firms adopt algorithms, higher prices are sustained. Furthermore, not all evidence points to collusion. Even when supracompetitive prices are sustained, there is a "robustness" issue with Q-learning algorithms (Abada et al., 2024)[29] where changes in competitor algorithms (den Boer, Meylahn & Schinkel, 2022)[30] and differences between the training and implementation environment (Eschenbaum, Mellgren & Zahn, 2022;[31] Asker, Fershtman & Pakes, 2024[32]) can cause supracompetitive prices to collapse. Finally, the algorithms can provide selective information to facilitate higher prices compared to simply sharing all information (Sugaya & Wolitzky, 2024).[33]

A related tacit collusion concern may originate from search and product ranking tools discussed in the FTC's surveillance

[24] Calvano, E., Calzolari, G., Denicolo, V., & Pastorello, S. (2020). Artificial intelligence, algorithmic pricing, and collusion. *American Economic Review*, *110*(10), 3267-3297.

[25] Faghani, H. (2025). Algorithmic Pricing, Market Outcomes, and Antitrust Concerns: Lessons from Recent Literature. *Market Outcomes, and Antitrust Concerns: Lessons from Recent Literature (February 25, 2025)*.

[26] Ballestero, G. (2025). Algorithmic Collusion Under Sequential Pricing and Stochastic Costs. *Available at SSRN 5203084*.

[27] Fish, S., Gonczarowski, Y. A., & Shorrer, R. I. (2024). *Algorithmic Collusion by Large Language Models. arXiv*.

[28] Assad, S., Clark, R., Ershov, D., & Xu, L. (2024). Algorithmic pricing and competition: empirical evidence from the German retail gasoline market. *Journal of Political Economy*, *132*(3), 723-771.

[29] Abada, I., Harrington Jr, J. E., Lambin, X., & Meylahn, J. M. (2024). Algorithmic collusion: where are we and where should we be going?. *Available at SSRN 4891033*.

[30] den Boer, A. V., Meylahn, J. M., & Schinkel, M. P. (2022). *Artificial collusion: Examining supracompetitive pricing by Q-learning algorithms* (No. TI 2022-067/VII). Tinbergen Institute Discussion Paper.

[31] Eschenbaum, N., Mellgren, F., & Zahn, P. (2022). Robust algorithmic collusion. *arXiv preprint arXiv:2201.00345*.

[32] Asker, J., Fershtman, C., & Pakes, A. (2024). The impact of artificial intelligence design on pricing. *Journal of Economics & Management Strategy*, *33*(2), 276-304.

[33] Sugaya, T., Stanford, G. S. B., & Wolitzky, A. (2024). Collusion with Optimal Information Disclosure.

pricing study (2024). Such tools may alter the consumer's search cost structure and offer potential benefits, such as mitigating the perceived "choice overload" through personalized rankings that prioritize products by predicted utility. However, Qiu et al. (2025) show that personalized ranking systems, while reducing search costs, may harm consumer welfare per se by enabling higher prices under algorithmic pricing. This occurs even in the absence of individualized price discrimination, as personalized rankings enhance the ability of Q-learning algorithms to sustain supra-competitive prices—thereby facilitating tacit price collusion. By contrast, Qiu et al. (2025) show that "unpersonalized" rankings, while increasing search costs, induce stronger price competition and enhance consumer welfare relative to personalized systems. Under standard economic analysis, any procompetitive justifications for personalized ranking tools must outweigh these potential harms to support a favorable competitive assessment.[34]

VI. Emerging ideas

A. New Criteria Are Needed Re: Surveillance and Algorithmic Pricing

Apart from privacy-related objections, the essence of surveillance pricing does not inherently contravene established antitrust doctrine. In practice, data will be collected, and pricing will increasingly reflect consumer-specific characteristics, especially in negotiated or dynamic pricing environments. The legal system offers limited grounds to challenge such practices absent exclusionary conduct, deception, or coordinated effects. However, when it comes to search and product ranking tools, the competitive and legal assessment diverges meaningfully. These tools can introduce artificial search costs, distort the consumer's choice architecture, and obscure relevant alternatives thereby impairing effective market access unless competitive benefits outweigh these harms.

In algorithmic pricing, it is amply clear that new criteria need to be developed as to what constitutes persistence *vis a vis* the length of supracompetitive algorithmic pricing in a particular matter, in addition to supra competitiveness of the prices. Measuring effectiveness (or "relevance"), robustness, sophistication, and speed vis a vis costs of learning are all areas where criteria need to be developed. For example, Q-learning is slow and not robust and likely starts to fail to sustain collusion when the number of competitors exceeds three. Alternatives such as Deep Q-learning algorithms and LLMs can sustain collusion but their robustness has not been studied (Abada et al., 2024). Thus, the new criteria should accommodate the type of algorithm as necessary.

B. Learning to Collude with No Human Interference

Most studies on emerging algorithmic collusion without human interference are based on controlled simulations,

[34] Qiu, L., Huang, Y., Singh, P. V., & Srinivasan, K. (2025). Personalization, consumer search, and algorithmic pricing. Marketing Science. Advance online publication. https://doi.org/10.1287/mksc.2023.0455.

demonstrating that algorithms can learn to sustain collusive outcomes autonomously. The EU treats such algorithms "[j]ust like an employee or an outside consultant" and holds the firms responsible for their actions.[35] The exact mechanism of learning tacit collusion is still unknown, but some evidence suggests that it is through the rewards and punishments (Calvano et.al., 2020). Further evidence suggests that even when the algorithm's rewards are set to be myopic, there can be collusive prices since the algorithms are learning from correlated data (Banchio & Mantegazza, 2025).[36] Thus, in addition to the potential confusion between price discrimination, tacit collusion and illegal collusion, Nazzini & Henderson (2024) point out that existing competition laws (EU and US) may be ill-equipped to deal with unintentional collusion from independently learning algorithms and systems where human oversight is minimal or absent.

C. *Differences in Algorithm Capabilities*

MacKay & Brown (2023) document that online retailers in the context of over-the-counter allergy drugs using different internal algorithms experience differences in speed and update intervals, suggesting asymmetries in the technology. Differences in algorithmic speed can alter pricing dynamics by enabling faster firms to credibly commit to reacting to rivals' prices in a manner that supports sustained supracompetitive pricing (MacKay & Brown, 2023).[37] Markups are shown to be higher than competitive, and the authors theoretically show that the asymmetries in the technology can give commitment power that help sustain high markups even without tacit collusion.

D. *New Plus Factors are Proposed as Evidence of Collusion*

Massarotto (2025) suggests some new plus factors to detect collusion more effectively: cryptography, private channels, and a minimum of four participants, as "the presence of price parallelism among a minimum of four participants makes a collusive scheme in a computer system tolerant to deviations from a common plan possible." These and other factors may need to be incorporated into enforcement strategies.

E. Algorithm Design and Rival Shorting as Collusion Remedies

Another new idea from Harrington (2025)[38] suggests that prohibiting data sharing hampers the algorithms along with their effectiveness, including the responsiveness of demand. Harrington (2025) shows that a third-party vendor in a hub-and-spoke algorithmic pricing system could rely solely on market data and a firm's own information and still induce

[35] Communication from the Commission, Guidelines on the applicability of Article 101 of the TFEU to horizontal co-operation agreements, OJ No C 259, 21.07.2023, p. 79.

[36] Banchio, M., & Mantegazza, G. (2022). Artificial intelligence and spontaneous collusion. *arXiv preprint arXiv:2202.05946*.

[37] Brown, Z. Y., & MacKay, A. (2023). Competition in pricing algorithms. *American Economic Journal: Microeconomics*, *15*(2), 109-156.

[38] Harrington Jr, J. E. (2025). A Critique of Recent Remedies for Third-Party Pricing Algorithms and Why the Solution is not Restrictions on Data Sharing. *Available at SSRN 5190097*.

supracompetitive pricing across clients. Instead, the focus should be on the targets or objective functions of the algorithms. One idea by Ayres et al. (2024),[39] "shorting rivals," which is used in the context of horizontal mergers, could be inspiring on how to "tame" the objectives of these algorithms. In conclusion, the source of harm is not the data being shared, but the shared objective embedded in the algorithm (Harrington, 2025).

F. Entry to Algorithm Market Could Be Encouraged

It is yet unexplored whether, as we suggested earlier, encouraging entry into the algorithm producer side, or offering free software would decrease the likelihood of collusive prices.

G. Transparency of the Algorithms Could Prove Essential

Nazzini & Henderson (2024) argue that regulatory frameworks should incorporate auditable AI mandates, ensuring transparency in algorithm design and operation adding that ex-ante controls must be prioritized, collaborative frameworks integrating legal, economic, and computer science expertise should be developed, and more empirical research needs to be conducted aiming the articulation of clear legal definitions for collusion arising from autonomous systems.

VII. Conclusion

Algorithmic pricing represents a significant transformation in how firms engage with market data, optimize revenue, and potentially interact with competitors offering paradoxical outcomes in terms of various types of economic efficiency. It involves cost-savings, improving productive efficiency and providing competitive benefits in the form of lower prices. Surveillance helps with personalized pricing or perfect price discrimination ("PPD"), which improves allocative efficiency via algorithmic pricing. These practices are generally lawful, that is, when they do not have anticompetitive effects such as exclusionary conduct. However, in PPD, prices to consumers are likely to increase on average and consumer surplus certainly decreases, which is a distributional concern drawing political attention, at the very least. Finally, the capacity of algorithms to monitor competitor behavior in real time, confirmed by various studies across a variety of environments and algorithm types, may create conditions under which tacit collusion may become more stable and less detectable, an anticompetitive effect that typically deteriorates allocative efficiency and reduces consumer surplus through higher prices. Thus, a possible outcome of the proliferation of algorithmic pricing is higher prices to consumers on average through price discrimination or tacit collusion, and clarifying the line between permissible and collusive behavior becomes imperative. This challenging mandate likely requires the support of

[39] Ayres, I., Hemphil, C.S., Wickelgren, A.L. (2024), Shorting Your Rivals: Negative Ownership as an Antitrust Remedy, 86 Antitrust L.J. 317.

different disciplines such as computer science and innovative regulation.