# Algorithmic Pricing Across Governance Contexts: An Economic Perspective with a Case Study on Behavioral Remedies in the DOJ–RealPage Settlement

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## 1. The Governance Context for Algorithmic Pricing

Algorithmic pricing is the practice by which firms automatically determine prices using advanced computational tools, including machine-learning and AI-powered software, that process market data, competitor pricing, and customer behavior. Algorithmic pricing often includes dynamic pricing, under which prices adjust over time in response to changing market conditions (MacKay et al., 2024).[37] In the evolution of market practices and business strategies, technological advancements typically manifest along a continuum, ranging from incremental improvements that subtly enhance existing methods to more disruptive innovations that fundamentally alter market dynamics. We believe surveillance technologies and algorithmic pricing have the potential to exemplify the latter category for reasons that we will address through economic foundations of pricing.[38] In other words, these tools represent not merely a refinement of traditional pricing and monitoring mechanisms but rather a paradigm shift with profound implications for competitive behavior, market transparency, and regulatory oversight. Their adoption introduces novel efficiencies, yet also raises significant concerns regarding collusion and price discrimination, thereby demanding a reassessment of existing antitrust frameworks.

The institutional landscape governing algorithmic and surveillance pricing comprises four distinct but interrelated modalities: legislation, regulation, antitrust enforcement, and judicial proceedings. Legislation operates at the foundational level, establishing or amending the legal framework within which market conduct is evaluated often in response to perceived gaps or emerging risks. Regulation follows as an administrative expression of legislative authority, deploying ex ante rules and supervisory tools to shape firm behavior before violations occur. Where regulation is absent, insufficient, or ineffective, antitrust enforcement functions as a primarily ex post mechanism, whereby competition authorities intervene to address specific instances of conduct alleged to harm market competition. Judicial proceedings then serve both as a forum for the adjudication of enforcement actions and as a venue for resolving challenges to the legality, scope, or application of legislative and regulatory instruments. These four components form a continuum of governance,

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[37] *MacKay, A. and Svartbäck, D. and Ekholm, A. G., Dynamic Pricing, Intertemporal Spillovers, and Efficiency (December 14, 2023). Harvard Business School Strategy Unit Working Paper, Available at SSRN: https://ssrn.com/abstract=4164271 or http://dx.doi.org/10.2139/ssrn.4164271.*

[38] *Surveillance pricing is a newer concept, which is a pricing regime dependent on inputs derived from meticulously following consumers virtually every move and across every possible platform, e.g., mouse movements while shopping online. Notably, the Federal Trade Commission (FTC) has initiated investigations into the competitive and consumer protection implications of such practices. Henceforth we focus on algorithmic pricing in general and consider surveillance pricing as an integral part of algorithmic pricing.*

ranging from rule creation to retrospective accountability, collectively shaping the competitive implications of technologically mediated pricing practices. So, we start by discussing legislative actions.

While scholars and practitioners set out to analyze and address these transformative shifts, legislative and enforcement bodies are concurrently grappling with the implications often responding in a reactive, and at times hasty, manner. In particular, algorithmic pricing has elicited growing scrutiny, with concerns that such mechanisms may facilitate tacit collusion or undermine price competition even absent explicit agreements. This reaction is understandable as discussed below. Nevertheless, there is still room for dispassionate analysis. The legislative developments mainly originate in the USA. At the U.S.A. federal level, Senator Amy Klobuchar introduced the Preventing Algorithmic Collusion Act in 2025, currently under committee review, which aims to explicitly prohibit the use of pricing algorithms to facilitate collusion, including tacit forms. At the U.S. state level, the New York Senate advanced the Algorithmic Pricing Disclosure Act (2025), expanding upon earlier proposals for transparency in surveillance-based pricing; while enforcement of this measure had initially been stayed in litigation brought before the Southern District of New York, it has since been upheld.

California is also advancing legislation that, according to reporting by The Capitol Forum (October 23, 2025), may subject "price recommendation services, especially in consumer-facing markets," to heightened antitrust scrutiny. Parallel legislative initiatives are emerging in Illinois, Texas, Massachusetts, Pennsylvania, New Jersey, Ohio, Vermont, and Maine, collectively signaling an intensifying legislative response to the antitrust risks posed by surveillance and algorithmic pricing practices. Next, we move on to regulation. In the domain of algorithmic pricing and surveillance pricing, as of late 2025, there is no "pure" regulation in the classic sense, i.e., general, binding, ex ante rules issued by an administrative agency with delegated legislative authority, that directly targets these practices as standalone subjects. The settlement proposal of the DOJ in DOJ v RealPage, which we discuss below, may signal some quasi-regulations that might be forthcoming. Next, we discuss antitrust enforcement.

While actual antitrust enforcement remains limited, regulators in the EU, UK, Japan, Canada, and others have issued guidance, launched market studies, and initiated public consultations to better understand the implications. The European Commission has clarified in its 2023 Horizontal Cooperation Guidelines that the use of shared algorithmic tools, particularly those relying on commercially sensitive data, may constitute unlawful information exchange under Article 101 TFEU. The UK's CMA and Japan's JFTC have similarly highlighted algorithmic hub-and-spoke arrangements and autonomous learning as enforcement priorities. Finally, Canada has launched targeted investigations and public consultations, including on algorithmic rent-setting and retail energy pricing. Finally, we discuss some judicial proceedings.

Legislative Actions are ex ante responses, in other words, they are forward-looking, whereas judicial proceedings are ex post mechanisms that address alleged violations in the past. Such proceedings start with the DOJ's 2010 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. Then, many other lawsuits followed.[39] In all the US cases, the government or private parties assert claims of illegal price-fixing and restraint of trade in violation of the Sherman Act, Section 1. Especially the RealPage Settlement proposal has a lot of economics-inspired elements, which we discuss below. Note that these cases are essentially motivated by higher observed prices, but higher prices can be the outcome of lawful or unlawful activities. To emphasize, there has been no antitrust enforcement case to date involving algorithmic pricing that addresses price discrimination in consumer markets. The only statutory avenue under U.S. federal law for challenging price discrimination is the Robinson-Patman Act, which applies exclusively to business-to-business (B2B) transactions involving commodities.

### 2. Clarifications of Efficiency Concepts in Economics in relation to Price Collusion and Price Discrimination

Productive 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. Algorithmic pricing can enhance productive efficiency through cost savings in pricing personnel, inventory, and capacity management, and may have procompetitive effects as such. We set aside productive efficiency going forward but note that it may be critical for arguments related to large scaled companies such as Amazon.

Allocative efficiency is the condition in which trade is unrestrained, ensuring that resources are allocated to their highest-valued uses in the economy. Consumer surplus represents the gains of

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

*[40] 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.*

*[41] Holt, B., Szyfer, C., Steinhauer, H. and Ottenberg, J., 2025 (October 1), Recent developments in algorithmic pricing: U.S. appeals court weighs in, enforcers stay aggressive, and open questions remain, available at https://www.hoganlovells.com/en/publications/recent-developments-in-algorithmic-pricing-us-appeals-court-weighs-in*

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

*[43] 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.*

*[44] Ge, Q. and Kim, M. and Kim, M., AI Adoption, Market Outcomes, and Coordination Risks (October 29, 2025). Available at SSRN: https://ssrn.com/abstract=5679104 or http://dx.doi.org/10.2139/ssrn.5679104*

consumers from trade and producer surplus represents the gains of producers from trade, more technically, their profits gross of fixed costs. Achieving allocative efficiency maximizes total surplus, which is the sum of consumer surplus and producer surplus. Allocative efficiency is independent of the distribution of the total surplus between consumers and producers.

It is well-established that price collusion leads to a deterioration in allocative efficiency. Where collusion is explicit, such conduct is per se unlawful in most jurisdictions. The present concern lies in the capacity of pricing algorithms to render tacit collusion more attainable. Although tacit collusion has the same adverse effect on allocative efficiency, it is not per se illegal. In contrast to explicit collusion, tacit collusion emerges through the mutual recognition of interdependence among firms (often modeled with game theory), absent any formal agreement or direct communication. Importantly, recent developments in EU and U.S. antitrust enforcement and jurisprudence suggest that the mode of collusion whether executed by human agents or by algorithms is largely immaterial and independent usage of the same third-party pricing software without an underlying agreement or confidential information sharing amongst the competitors is not illegal.[40,41]

A hub-and-spoke system refers to a structure in which the underlying algorithms aggregate data from all participating firms, thereby obtaining more precise information regarding cost and demand shocks in the market. The algorithm subsequently provides individualized pricing recommendations to each firm. There is some empirical evidence of tacit price coordination in the airline industry, even though many carriers still employ pricing heuristics rather than fully dynamic AI models, suggesting that tacit collusion may become more effectively sustained through algorithmic pricing.

In some instances, firms deploy pricing algorithms independently, yet such use can still give rise to collusive outcomes. A commonly employed class of algorithms is Q-learning, a type of reinforcement learning algorithm that determines optimal actions by iteratively updating value estimates through trial-and-error interactions, with the objective of maximizing long-term rewards. In a seminal simulation study, Calvano et al. (2020) demonstrated that Q-learning algorithms can readily learn to collude absent any explicit communication akin to the behavior of human executives.[42] For instance, these algorithms may implement strategies involving temporary punishment of price-cutting behavior followed by a gradual return to elevated prices, effectively replicating the "tit-for-tat" strategy known to sustain tacit collusion.

Empirical evidence of supracompetitive prices is limited at the moment. For example, Assad et al. (2022) present such evidence from the German retail gasoline market that in a duopoly where both firms adopt algorithms, higher prices are sustained.[43] Furthermore, not all available evidence points to successful and sustained collusion. Ge et al. (2025) find that AI adoption is associated with a 2.4% increase in average fares, some but not all attributed to quality improvements, the remaining part more consistent with coordination channels.[44] Next, we move to a potentially even more controversial effect of algorithmic pricing, what is, in practice, called "revenue" or "yield" management as revenue management almost always entails a form of "price discrimination."

Surveillance of consumers via price targeting or consumer segmentation and profiling tools allows firms to determine all these relevant inputs and hence their willingness to pay (WTP) for a particular product or service at given locations, times, and sales channels. The practice of charging different prices to different consumers or consumer groups based on their WTP is called price discrimination, and surveillance pricing makes this practice much easier. In perfect price discrimination (PPD), a seller charges each buyer their maximum WTP, capturing all of the consumer surplus. Marinova and Bergqvist (2025) warn that AI-driven price discrimination may harm consumers.[45] Consistent with theory, Dubé and Misra (2023) show for an online platform that matches job seekers with employers that average consumer surplus declines by 23% with algorithmic pricing, even though the consumers who join the market may still pay less than the previously prevailing uniform price.[46]

Price discrimination may fail when secondary markets emerge or competition leads to successful price undercutting. It works best with product differentiation, switching costs, price search costs, and no capacity constraints, If a firm is successful in perfect price discrimination, then consumer surplus declines to zero, but this decline typically does not harm competition. Moreover, PPD improves allocative efficiency. This characteristic is one of the reasons why price discrimination is generally not illegal. From a foundational economic perspective, this situation represents the emergence on dedicated markets for each consumer where price is determined by bilateral bargaining rather an auction. The emergence of markets are consistent with the completeness assumption of the first fundamental welfare theorem, as such allocative efficiency follows. On the other hand, price determination via bargaining affects only the distribution of the surplus to be gained from bilateral trade. Ecer (2025) discusses deeper aspects of price discrimination in algorithmic pricing.[47]

### 3. A Case Study: The Behavioral Remedies in the DOJ's Settlement Proposal in RealPage

It is amply clear by now that algorithmic pricing requires new criteria and monitoring in terms of facilitating price collusion. There are several emerging ideas discussed in Ecer and Ekmekci (2025).[48] In this article, we lay out and discuss the elements of the settlement proposal of the DOJ in the RealPage matter as it relates to our thinking.[49,50] Most of the items are about decreasing the scope for collusion by putting in more friction. The economically relevant behavioral remedies in the settlement proposal and our comments are as follows:

i. "Cease having its software use competitors' nonpublic, competitively sensitive information to determine rental prices in runtime operation;"

- This measure directly targets hub-and-spoke collusion, where a central platform may use private inputs from multiple firms to generate interdependent pricing suggestions. In economic models, lack of information sharing hinders collusion hampering mutual monitoring, destabilizing collusion (Green & Porter, 1984; Abreu, 1988).[51,52]

ii. "Cease using active lease data for purposes of training the models underlying the software, limiting model training to historic or backward-looking nonpublic data that has been aged for at least 12 months;"

- This criterion aims to limit the algorithm's learning speed and relevance, thereby reducing its ability to forecast and coordinate with competitors' current strategies. Using aged data dilutes the strategic value of training inputs and increases informational frictions, which are central to preventing tacit collusion in repeated-game models.

iii. "Not use models that determine geographic effects narrower than at a state level, which is broader than the markets alleged in the complaint;"

- This targets the granularity of market segmentation. Collusion is often easier to sustain in narrower, more homogeneous markets (i.e., with fewer firms, stable demand). Prohibiting micro-level geographic modeling blurs market-specific demand and supply signals, raising coordination costs. In economic terms, this restriction raises noise in the signal extraction process, which Green & Porter (1984) show can disrupt self-enforcing collusive strategies. This remedy may also hamper price discrimination indirectly.

iv. "Remove or redesign features that limited price decreases or aligned pricing between competing users of the software;"

- This directly targets alignment mechanisms. Features that resist price cuts or guide users toward similar pricing effectively soften competition and create a focal point for coordination. Such design elements simulate "facilitating practices" akin to most-favored-nation clauses or uniform pricing policies, which reduce incentives to deviate. Their removal restores firms' autonomy and reintroduces incentives to undercut, increasing the instability of collusion.

v. "Cease conducting market surveys to collect competitively sensitive information;"

- Economic models emphasize that observability and monitoring are prerequisites for sustaining collusion. Prohibiting such surveys reintroduces opacity into competitive conditions and reduces the ability of firms (or the platform) to detect and punish deviations.

vi. "Refrain from discussing market analyses or trends based on nonpublic data, or pricing strategies, in RealPage meetings relating to revenue management software."

- Strategic discussions can foster a shared understanding or signaling environment, which economic literature classifies as a "plus factor" for establishing collusion. Limiting such discussions removes soft coordination cues, reducing mutual awareness and the likelihood of coordinated expectations.

As the DOJ's behavioral remedies demonstrate, enforcement is likely to intensify in the realm of algorithmic pricing, given the perceived potential for increased price collusion and discriminatory practices that threaten not only digital markets but also traditional sectors increasingly reliant on data-driven pricing, blurring the line between efficiency-enhancing innovation and conduct that may distort competitive outcomes.

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

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

[47] *Ecer, S., The Political Economy of Widespread Algorithmic Retail Price Discrimination, The Forum Newsletter (The Capitol Forum, Dec. 6, 2025).*

[48] *Ecer, S. & Ekmekci, M., Between Efficiency and Illegality: The Competitive Implications of Surveillance and Algorithmic Pricing, CPI Columns, Aug. 6, 2025.*

[49] *United States v. RealPage, Inc., No. 1:24-cv-00710-WLO-JLW (M.D.N.C. proposed final judgment filed 2024). See U.S. Department of Justice, Justice Department Requires RealPage to End Sharing of Competitively Sensitive Information and Adopt Antitrust Compliance Measures, Office of Public Affairs (Nov. 3, 2023), https://www.justice.gov/opa/pr/justice-department-requires-realpage-end-sharing-competitively-sensitive-information-and*

[50] *For a legal interpretation of the settlement see Holt, B., Phibbs, L., Steinhauer, H. and Ottenberg, J., 2025 (December 5), Proposed DOJ settlement provides guidance on use of competitive information in algorithmic pricing tools, available at https://www.hoganlovells.com/en/publications/proposed-doj-settlement-provides-guidance-on-use-of-competitive-information*

[51] *Green, E. J., & Porter, R. H. (1984). Noncooperative Collusion under Imperfect Price Information. Econometrica, 52(1), 87–100*

[52] *Abreu, D. (1988). On the Theory of Infinitely Repeated Games with Discounting. Econometrica, 56(2), 383–396.*