

NOTES

REORGANIZING THE REGULATORY TOOLBOX: A NEW FRAMEWORK FOR THE COMPETITIVE IMPLICATIONS OF ALGORITHMIC PRICING

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Prices for consumer goods as wide-ranging and essential as groceries, over-the-counter drugs, and rental housing are now commonly set by automated algorithmic systems, which process enormous volumes of data to rapidly adjust prices in response to market conditions. Antitrust regulators have raised concerns that these systems can be used, intentionally or inadvertently, to facilitate anticompetitive collusion, ultimately harming consumers by raising prices and reducing competition on the merits. In this Note, I argue that the imposition of a collusion framework designed around human behavior is misguided, and that algorithmic systems should instead be analyzed in terms of their structural characteristics. By thinking of pricing algorithms in terms of traits like strategic commitment, the scope of data use, and platform intermediation, regulators can better understand the true extent of algorithm-driven pricing harms and design more effective, targeted regulations to address them.

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INTRODUCTION

Algorithmic pricing—the use of price-setting decisions made primarily by automated systems—has become ubiquitous in consumer markets. Used for decades by airlines and hotels to match prices to demand fluctuations, algorithmic pricing is now taking over online and offline retail, event ticketing, and even the brick-and-mortar restaurant industry.¹ For businesses, algorithmic tools radically reduce the managerial burdens of pricing large and diverse product portfolios, calculating responses to changing supply and labor costs, and quickly reacting to variations in consumer demand.² Particularly after the supply volatility and shifts to online consumption of the COVID-19 pandemic, many retailers now cite the high-frequency price updates enabled by algorithmic systems as a necessity for staying competitive and in business.³

But the outsourcing of pricing decisions to hyper-responsive, impersonal automated systems can also enable a wide range of consumer

¹ See Oliver Barnes, Philip Georgiadis & Laura Onita, *The Rise of Surge Pricing: ‘It Will Eventually Be Everywhere,’* FIN. TIMES (Sep. 15, 2023), <https://www.ft.com/content/d0e3bcb5-b824-414e-bfac-4c0b4193e9f0> [<https://perma.cc/4BSL-MY9G>] (reporting wide adoption of algorithmic pricing in the United States and use by twenty to forty percent of retailers in major European markets); *5th Annual State of Digital for Enterprise QSR & Fast Casual Brands*, QU, <https://www.qubeyond.com/2024-5th-annual-state-of-digital-for-qsr-amp-fast-casual-brands> [<https://perma.cc/7MYD-JC9T>] (last visited Oct. 12, 2025) (surveying 62,000 U.S. fast-casual restaurant locations and finding that thirty-nine percent of respondents named dynamic pricing a top business priority for 2024).

² See Barnes, Georgiadis & Onita, *supra* note 1; Charity L. Scott, *Shoppers Are Caught Off Guard as Prices of Everyday Items Change More Often*, WALL ST. J. (Feb. 4, 2022, at 05:30 ET), <https://www.wsj.com/articles/shoppers-are-caught-off-guard-as-prices-on-everyday-items-change-more-often-11643970606> [<https://perma.cc/G3VY-U66W>] (citing retailers explaining the benefits of algorithmic pricing).

³ See Scott, *supra* note 2 (citing several owners of retail stores and supermarkets on their increasingly frequent price updates).

harms, from price gouging and instability to algorithm-facilitated cartels that artificially reduce competition. In early 2024, the fast-food chain Wendy's announced plans to implement dynamically changing prices, sparking fears of unpredictable, Uber-like "surge pricing" for simple food items.⁴ A December 2025 report revealed that online grocery marketplace Instacart conducted algorithmic pricing experiments resulting in different per-customer prices for identical items, prompting an FTC investigation and legislative backlash.⁵ And for the last two years, the Department of Justice and eight state attorneys general have pursued a civil suit against rental pricing software developer RealPage and several major rental housing providers, alleging that RealPage's pricing algorithm helped landlords coordinate business strategies in order to artificially inflate rents and deprive tenants of a competitive housing market.⁶

This Note focuses specifically on the anticompetitive effects of algorithmic pricing: those that undermine competitors' ability or incentive to meet demand, thereby disengaging pricing and production from consumer preference and ultimately harming consumer welfare.⁷

⁴ See Joe Hernandez, *No, Wendy's Says It Isn't Planning to Introduce Surge Pricing*, NPR (Feb. 28, 2024, at 05:18 ET), <https://www.npr.org/2024/02/28/1234412431/wendys-dynamic-surge-pricing> [<https://perma.cc/SU99-NMCK>] (noting that dynamic pricing could also be used to provide discounts at less popular times of day).

⁵ See Derek Kravitz, *Instacart's AI-Enabled Pricing Experiments May Be Inflating Your Grocery Bill, CR and Groundwork Collaborative Investigation Finds*, CONSUMER REPS. (Dec. 22, 2025), <https://www.consumerreports.org/money/questionable-business-practices/instacart-ai-pricing-experiment-inflating-grocery-bills-a1142182490> [<https://perma.cc/M7X9-5NSD>]; Derek Kravitz, *Instacart Stops Pricing Tests on Its Customers Amid Outrage from Customers*, CONSUMER REPS. (Jan. 8, 2026), <https://www.consumerreports.org/money/questionable-business-practices/instacart-stops-ai-pricing-experiments-a1176475852> [<https://perma.cc/3MW6-SJ9S>].

⁶ Amended Complaint at 1–2, *United States v. RealPage, Inc.*, No. 1:24-cv-00710 (M.D.N.C. filed Jan. 7, 2025) [hereinafter *U.S. v. RealPage Amended Complaint*]. In November 2025, the Department of Justice announced that it had agreed to settle its claims against RealPage. See Proposed Final Judgment, *United States v. RealPage, Inc.*, No. 1:24-cv-00710 (M.D.N.C. Nov. 24, 2025), Dkt. No. 159-1 [hereinafter *U.S. v. RealPage Proposed Final Judgment*]; see also *infra* notes 171–73 and accompanying text for more discussion.

⁷ "Competition" and its corollary terms "anticompetitive" and "procompetitive" are broadly and often indistinctly defined in the legal literature. See generally Daniel Francis, *Antitrust Without Competition*, 74 DUKE L.J. 353 (2024) (arguing that the use of "competition" without a clear definition creates a confusing and misleading legal standard). In this Note, I largely ground discussions of competition in the consumer welfare standard commonly used by courts today. See, e.g., *NCAA v. Bd. of Regents of Univ. of Okla.*, 468 U.S. 85, 107 (1984) (describing a situation where "[i]ndividual competitors lose their freedom to compete [, p]rice is higher and output lower than they would otherwise be, and both are unresponsive to consumer preference" as anticompetitive and counter to the Sherman Act's "consumer welfare prescription"); see also PHILLIP AREEDA, LOUIS KAPLOW, AARON EDLIN & C. SCOTT HEMPHILL, *ANTITRUST ANALYSIS: PROBLEMS, TEXTS, AND CASES* 29 (8th ed. 2022) (listing behavioral criteria for a practicably competitive market, including that firms should make price and output decisions independently and compete "on the merits"). In-depth discussion

Traditionally, antitrust law addresses welfare harms by prohibiting certain volitional conduct, such as coordinated price-setting, that tends to produce these effects.⁸ But pricing algorithms, which lack inherent regard for legal conventions and run on machine-generated rules that can defy meaningful human interpretation,⁹ create a functional separation between human-made business decisions and a firm's actual pricing behavior. Firms engaged in algorithmic profit maximization might exploit unexpected market features unrelated to efficiency or demand, and they might even—intentionally or inadvertently—coordinate prices instead of competing on them.¹⁰ This separation threatens to destabilize longstanding norms of competitive conduct: Algorithmic pricing weakens the causal connection between human volition and market action, blurring the lines between lawful vigorous competition and unlawful delegated coordination and opening new avenues for unchecked profit-seeking to consumers' detriment.¹¹

In response, regulators and legal scholars have fixated on forms of algorithm-enhanced coordination that test the bounds of traditionally prohibited conduct, proposing fundamental expansions of antitrust doctrine to bring these threats more firmly within the reach of the law.¹² Numerous academics have sounded the alarm on “algorithmic tacit collusion,” in which firms acting seemingly independently deploy

of market-responsive pricing effects, like surge pricing and lawful price discrimination, is outside of the scope of this Note.

⁸ See *infra* Section I.B for discussion of the negative impacts of price coordination on consumer welfare.

⁹ See *infra* Section I.A for discussion of algorithmic explainability problems.

¹⁰ See generally Organisation for Economic Co-operation and Development [OECD], *Algorithms and Collusion: Competition Policy in the Digital Age*, at 7–8 (2017) [hereinafter OECD, *Algorithms and Collusion*], <https://web-archiver.oecd.org/2019-02-17/449397-Algorithms-and-collusion-competition-policy-in-the-digital-age.pdf> [<https://perma.cc/8KGG-8F27>] (discussing new competitive risks posed by algorithmic price coordination and surveying potential regulatory responses).

¹¹ See *id.*

¹² See, e.g., Terrell McSweeney & Brian O’Dea, *The Implications of Algorithmic Pricing for Coordinated Effects Analysis and Price Discrimination Markets in Antitrust Enforcement*, 32 ANTITRUST 75, 79 (2017) (“Increasingly autonomous and sophisticated algorithmic pricing raises novel challenges to which antitrust enforcers must adapt.”); Margrethe Vestager, Comm’r for Competition, Eur. Comm’n, Speech at the Bundeskartellamt 18th Conference on Competition (Mar. 16, 2017) [hereinafter Vestager Speech] (“[W]hen we look at the challenges for cartel enforcement in the future, one of the biggest things we need to deal with is the risk that automated systems could lead to more effective cartels.”); Organisation for Economic Co-operation and Development [OECD], *Algorithmic Competition: OECD Competition Policy Roundtable Background Note*, at 15, OECD Doc. DAF/COMP(2023)3 (2023) [hereinafter OECD, *Algorithmic Competition*], <https://www.oecd.org/daf/competition/algorithmic-competition-2023.pdf> [<https://perma.cc/L3KE-M8KK>] (proposing changing the definitions of “agreement” and “concerted practice” to better capture harmful cases of algorithmic collusion).

pricing algorithms that nevertheless interact to produce coordinated supracompetitive prices.¹³ Because Section 1 of the Sherman Act requires an agreement—a “contract, combination . . . or conspiracy[] in restraint of trade”¹⁴—and because of the economic risks of chilling vigorous but independent competition, courts have long held such “tacit” coordination to be lawful.¹⁵ However, many antitrust scholars and policymakers, concerned with the scale of consumer harms that might arise if algorithmic tacit collusion becomes widespread, have begun to propose expansions of the Section 1 agreement requirement to cover new algorithmic interactions, as well as far-reaching extensions of liability to the designers of collusive algorithms.¹⁶ Others, taking note of rapid technological progress in consumer-ready artificial intelligence, have begun to view certain advanced algorithms as autonomous economic agents, with some even advocating for the imputation of criminal intent to these systems.¹⁷ Some academics, looking still further,

¹³ See *infra* Section I.B for more background on collusion.

¹⁴ Sherman Act of 1890 § 1, 15 U.S.C. § 1. EU competition law is also designed around agreements, barring “all agreements between undertakings . . . and concerted practices which may affect trade between Member States and which have as their object or effect the prevention, restriction, or distortion of competition within the internal market.” Consolidated Version of the Treaty on the Functioning of the European Union art. 101, May 9, 2008, 2008 O.J. (C 115) 88–89 [hereinafter TFEU].

¹⁵ See *In re* Text Messaging Antitrust Litig., 782 F.3d 867, 874 (7th Cir. 2015) (noting that tacit collusion is not a Sherman Act violation “and probably shouldn’t be”); Organisation for Economic Co-operation and Development [OECD] Competition Comm., *Algorithms and Collusion – Note from the European Union*, at 5–6, OECD Doc. DAF/COMP/WD(2017)41 (June 14, 2017) [hereinafter *EU Submission on Algorithms and Collusion*], [https://one.oecd.org/document/DAF/COMP/WD\(2017\)12/en/pdf](https://one.oecd.org/document/DAF/COMP/WD(2017)12/en/pdf) [<https://perma.cc/V4C4-ZDER>] (stating that Article 101 of the TFEU permits tacit collusion, leaving “[e]very producer . . . free to change his prices, taking into account in or so doing the present or foreseeable conduct of his competitors”). U.S. courts tend to only impose liability if there is “evidence that tends to exclude the possibility that the [firms] were acting independently,” typically some form of overt communication. See Joseph E. Harrington, Jr., *Developing Competition Law for Collusion by Autonomous Artificial Agents*, 14 J. COMPETITION L. & ECON. 331, 337–39, 349 (2019) [hereinafter Harrington, Jr., *Developing Competition Law*] (quoting *Monsanto Co. v. Spray-Rite Serv. Corp.*, 465 U.S. 752, 765 (1984)).

¹⁶ See, e.g., OECD, *Algorithmic Competition*, *supra* note 12, at 15 (proposing expansions to the definition of “agreement”); Ariel Ezrachi & Maurice E. Stucke, *Sustainable and Unchallenged Algorithmic Tacit Collusion*, 17 NW. J. TECH. & INTELL. PROP. 217, 258–59 (2020) [hereinafter Ezrachi & Stucke, *Algorithmic Tacit Collusion*] (arguing that regulators should pay more attention to the collusive behavior of algorithms and consider extending liability to algorithm designers).

¹⁷ See Sara Fish, Yannai A. Gonczarowski & Ran Shorrer, *Algorithmic Collusion by Large Language Models 2* (Sep. 8, 2025) (arXiv manuscript), <https://arxiv.org/abs/2404.00806> [<https://perma.cc/9V57-75ZH>] (viewing large language models as “a completely new kind of economic agent, worthy of separate behavioral analysis”); Aslihan Asil & Thomas G. Wollmann, *Can Machines Commit Crimes Under U.S. Antitrust Laws?*, 3 U. CHI. BUS. L. REV. 1, 27–34 (2023) (arguing that large language models can possess the criminal intent to collude). For background on large language models, see *infra* note 37 and accompanying text.

have argued that the possibility of fully autonomous algorithmic control of markets poses an existential threat to competition itself as the foundation of the modern economy.¹⁸

In this Note, I argue that legal scholars, acting on a misguided instinct to analyze algorithmic systems through frameworks based on human behavior, have focused too narrowly on the idea of algorithmic enhancement of traditional collusive conduct. Instead, a structural analysis of these systems reveals both that algorithms can suppress competition and harm welfare in ways that bear little resemblance to collusion, and their behavior is rooted in underlying design mechanics that can be regulated with tools beyond antitrust. Algorithmic systems are neither simple digital interfaces for the straightforward execution of human business decisions nor true agents governed by rational incentives. Their operational behavior emerges from a set of functional constraints, including restricted and easily replicable strategies, a defined set of discrete data inputs, and the design choices and market incentives of third-party platforms. Regulators looking to move beyond the limitations of antitrust and more effectively address algorithmic welfare harms should target their interventions at the real-world structural features of these systems, not speculative models of their conduct based on human behavioral assumptions.

This Note proceeds in four parts. Part I provides some background on artificial intelligence and economic theory, showing how these systems' vast capacity for information processing threatens to disrupt economic assumptions about competitive markets. Part II highlights the current academic tendency to view pricing algorithms through an antitrust-influenced conduct lens tightly focused on collusion and discusses some of the limitations of enforcement and policy efforts tied to this view. In Part III, drawing on research across economics, computer science, and law, I discuss three features distinguishing algorithmic pricing systems from human-led strategies: long-term commitment allowing for fixed patterns of interaction, reliance on defined input data with limited scope, and distribution via third-party intermediaries. I show how a systems-oriented analysis reveals the inability of conduct-based frameworks to grapple with the full scope of potential algorithmic pricing harms. Finally, in Part IV, I briefly consider how these three structural factors provide a basis for clearer analysis of various regulatory tools, including antitrust but also targeted regulations of data use and platform design.

¹⁸ See, e.g., Daniel A. Crane, *Antitrust After the Coming Wave*, 99 N.Y.U. L. REV. 1187, 1236–40 (2024) (contemplating a world where artificial intelligence systems control markets and economic production entirely autonomously, obviating the need for competition, with regulators relegated to auditing systems to ensure “a more socially-minded mission”).

I

BACKGROUND: ALGORITHMS IN THE MARKET

Advancements in data processing and artificial intelligence over the last decade have transformed the business landscape. Firms equipped with increasingly capable algorithmic systems can efficiently process enormous volumes of data about their products, customers, and competitors, undoubtedly creating market efficiencies but also upending some of the longstanding assumptions that underpin antitrust theory. In the absence of comprehensive empirical case studies of algorithmic operation and effects,¹⁹ legal and economic scholarship has largely focused on the ways in which these systems might facilitate known forms of anticompetitive conduct. In this Part, I provide some brief technical background on pricing algorithms and discuss some of the theorized impacts of their use in competitive markets.

A. Pricing Algorithms and Artificial Intelligence

Millions of businesses now use systems ranging from simple automated rules to complex artificial intelligence programs, all lumped under the term “algorithm.” Traditionally, and intuitively, an algorithm is a sequence of instructions performed to carry out a given task. I refer to algorithms meeting this basic definition as *simple algorithms*. In the pricing context, they might include rule-based instructions like “match competitor A’s lowest price, unless it drops below our minimum” or “raise prices for customer B if they toggle away from and back to our website.”²⁰ These algorithms generally behave deterministically, with easily testable outputs,²¹ and they can typically be effectively audited via inspections of source code.²² Simple algorithmic pricing tools are

¹⁹ See OECD, *Algorithmic Competition*, *supra* note 12, at 14–15 (summarizing the few empirical studies and court cases involving algorithmic collusion).

²⁰ See Leon Musolff, *Algorithmic Pricing, Price Wars and Tacit Collusion: Evidence from E-Commerce* 12 (Mar. 27, 2024) (unpublished manuscript), https://lmusolff.com/papers/Algorithmic_Pricing.pdf [<https://perma.cc/C52T-Q57B>] (illustrating a typical third-party pricing system used on the Amazon marketplace, with options enabling sellers to match the lowest competing price, always match Amazon’s own price, automatically raise prices to a preset maximum in the absence of competition, and more); Philip Hanspach, Geza Sapi & Marcel Wieting, *Algorithms in the Marketplace: An Empirical Analysis of Automated Pricing in E-Commerce*, 69 INFO. ECON. & POL’Y 1, 2–3 (2024) (depicting a simple rule-based system used on the Dutch online marketplace Bol.com).

²¹ See BEN BUCHANAN & TAYLOR MILLER, *MACHINE LEARNING FOR POLICYMAKERS* 5 (2017) (contrasting early efforts at artificial intelligence, which involved “clear preset rules with fixed conditions,” with machine learning programs).

²² But even algorithms built around individual logically simple rules can become enormously complex as rules are added and combined to handle increasingly specific input cases or output behaviors. See Renato Nazzini & James Henderson, *Overcoming the Current*

offered as a user feature by most major online marketplaces like Amazon and eBay, as well as by numerous third-party pricing providers that cater to sellers on these major platforms.²³ Though the exact popularity of these algorithms is difficult to measure, one study of 2018 data from a Dutch online marketplace found that over eighty percent of products with three or more total sellers featured at least one seller using simple repricing tools,²⁴ and a 2020 study of a single third-party pricing provider on Amazon found over 55,000 unique sellers in that provider's customer data.²⁵

Machine learning models involve newer computing techniques that enable algorithms to take in more complex data and adapt their outputs to changing conditions.²⁶ Several components control the behavior of a machine learning model: the learning program, which is a mathematical algorithm that models a method of solving a type of problem; the input data, which describes a specific instance of that problem for which to output a response; and, in many methods, the training data, used to “teach” the algorithm an overall problem context.²⁷ Different models can be produced by executing the same learning program on different training data, and these models can be distributed for independent use on different users' input data. For example, the pricing system at issue in *RealPage* used machine learning to create supply and demand models based on training data obtained from landlords.²⁸ These models could

Knowledge Gap of Algorithmic “Collusion” and the Role of Computational Antitrust, 4 STAN. COMPUTATIONAL ANTITRUST 1, 27 (2024) (describing how technical audits of source code can “read [an algorithm’s] mind” but noting that code analysis is typically ineffective for more complex or machine learning-based algorithms).

²³ Qiaochu Wang, Yan Huang, Param Vir Singh & Kannan Srinivasan, *Algorithms, Artificial Intelligence, and Simple Rule-Based Pricing 2* (Apr. 14, 2023) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4144905 [<https://perma.cc/XH3L-FBLQ>] (explaining that most major e-commerce marketplaces offer simple pricing tools for free to users of their platforms).

²⁴ See Hanspach, Sapi & Wieting, *supra* note 20, at 7 fig. 4 (reporting at least one algorithmic seller in over eighty percent of observations of products with three or more sellers).

²⁵ See Musolf, *supra* note 20, at 9 (describing a dataset with 102,849 unique products and 55,121 unique merchants).

²⁶ See BUCHANAN & MILLER, *supra* note 21, at 5–6.

²⁷ See Competitive Impact Statement at 15, *United States v. RealPage, Inc.*, No. 24-cv-00710 (M.D.N.C. Nov. 24, 2025), Dkt. No. 160 [hereinafter *U.S. v. RealPage Competitive Impact Statement*] (“Models are trained using data to define and refine the rules or instructions by which they operate.”). See generally BUCHANAN & MILLER, *supra* note 21, at 5–11 (providing an overview of machine learning techniques geared towards policymakers).

²⁸ *U.S. v. RealPage Amended Complaint*, *supra* note 6, at 17–21 (describing RealPage's price recommendation system); *U.S. v. RealPage Competitive Impact Statement*, *supra* note 27, at 15 (providing more detail on RealPage's supply and demand models). See also *infra* notes 89–92 and accompanying text for further discussion of the legal significance of training data.

then be applied to input data describing a specific property in order to create pricing recommendations for that property.²⁹

One subtype of machine learning commonly used by economics researchers in market simulations is *reinforcement learning*, in which a model, guided by its learning program, “explores” an environment, like a given market, by experimenting with various actions, like setting different prices.³⁰ Eventually, the model gains enough context about the environment that it can competently respond to new inputs in order to solve some overall problem, like maximizing its profit.³¹ Reinforcement learning can be particularly useful for complex environments where conditions change rapidly in response to each output decision: In ridesharing markets, for example, price changes affect driver supply and rider demand simultaneously.³² Both Uber and Lyft use reinforcement learning methods to match drivers and riders on their marketplaces.³³

The most computationally capable machine learning models are *deep learning models*, which use a layered algorithmic architecture in the learning program to efficiently process vastly larger volumes of data and learn far more complex strategies than simpler models.³⁴ However, despite intense academic interest and some experimentation at large firms,³⁵ deep learning models designed specifically for pricing

²⁹ U.S. v. RealPage Amended Complaint, *supra* note 6, at 17–21.

³⁰ See OECD, *Algorithmic Competition*, *supra* note 12, at 14 (noting that “algorithmic autonomous tacit collusion is usually modelled using reinforcement learning algorithms”); John Asker, Chaim Fershtman & Ariel Pakes, *Artificial Intelligence and Pricing: The Impact of Algorithm Design* 9–15 (Nat’l Bureau of Econ. Rsch., Working Paper No. 28535, 2021) (detailing the design and parameters of a typical reinforcement learning algorithm in an economic modeling context); *see also* Emilio Calvano, Giacomo Calzolari, Vincenzo Denicolò & Sergio Pastorello, *Artificial Intelligence, Algorithmic Pricing, and Collusion*, 110 AM. ECON. REV. 3267 (2020) [hereinafter Calvano et al., *Artificial Intelligence*] (using reinforcement learning algorithms to simulate competing firms). Reinforcement learning algorithms are also commonly used in multiplayer games. *See, e.g., AlphaGo*, GOOGLE DEEPMIND, <https://deepmind.google/technologies/alphago> [<https://perma.cc/S5CC-3SWS>] (last visited Oct. 12, 2025).

³¹ *See* BUCHANAN & MILLER, *supra* note 21, at 5–11.

³² *See* Zhiwei (Tony) Qin, Hongtu Zhu & Jieping Ye, *Reinforcement Learning for Ridesharing: An Extended Survey*, 144 TRANSP. RSCH. PART C, no. 103852, 2022, at 1, 6 (reviewing studies of reinforcement learning for ridesharing pricing).

³³ *See generally* Xabi Azaguirre et al., *A Better Match for Drivers and Riders: Reinforcement Learning at Lyft*, 54 INFORMS J. ON APPLIED ANALYTICS 71, (2024) (describing Lyft’s use of reinforcement learning); Prateek Jain, Soheil Sadeghi & Mehrdad Bakhtiari, *Reinforcement Learning for Modeling Marketplace Balance*, UBER BLOG (July 2, 2025), <https://www.uber.com/blog/reinforcement-learning-for-modeling-marketplace-balance> [<https://perma.cc/9XWK-K7LD>] (same for Uber).

³⁴ *See* BUCHANAN & MILLER, *supra* note 21, at 14–15 (providing an overview of deep learning algorithms).

³⁵ *See, e.g.,* Jiaxi Liu, Yidong Zhang, Xiaoqing Wang, Yuming Deng & Xingyu Wu, *Dynamic Pricing on E-Commerce Platform with Deep Reinforcement Learning: A Field Experiment 2* (Aug. 31, 2021) (arXiv manuscript), <https://arxiv.org/abs/1912.02572> [[https://](https://arxiv.org/abs/1912.02572)

remain uncommon in commercial practice.³⁶ Today, the most significant advancements in artificial intelligence are taking place with *large language models* (LLMs), popularized by services like ChatGPT, which are deep learning models optimized to generate statistically likely human-language output.³⁷ Though the full extent of their capabilities remains ill-defined, the interactivity, flexibility, and off-the-shelf availability of LLMs has spurred substantial interest in using them for numerous generalized tasks, including pricing.³⁸

As algorithmic systems rapidly develop in size and complexity, a major policy concern is that they may behave in ways that are unanticipated and unexplainable by humans.³⁹ While the behavior of simple rule-based algorithms can be inspected straightforwardly, code and data audits provide minimal interpretability for machine learning and deep learning models. These systems, particularly large deep learning models, behave as “black boxes,” with outputs affected by up to billions of mathematical interactions, sometimes random, between the learning algorithm, the input data, and the training data.⁴⁰ Because of these many layers of mathematical operations, meaningfully tracing the effect of any one subset of that data on the behavior of the model is extremely difficult. Current approaches to explaining the behavior of

perma.cc/DQ7N-GJKC] (presenting pricing experiments with deep reinforcement learning by researchers at Chinese e-commerce platform Tmall).

³⁶ See Elias Dritsas & Maria Trigka, *Machine Learning in E-Commerce: Trends, Applications, and Future Challenges*, 13 IEEE ACCESS 99048, 99055–56 (2025) (discussing the challenges of using deep learning models, which “demand substantial computational resources” and for which frequent retraining is “computationally prohibitive,” in fast-moving e-commerce settings); Wang et al., *supra* note 23, at 2–3 (noting that little empirical evidence exists for the use of complex reinforcement learning pricing algorithms in practice and citing Liu et al., *supra* note 35, as a sole example).

³⁷ See generally Shervin Minaee, Tomas Mikolov, Narjes Nikzad, Meysam Chenaghlu, Richard Socher, Xavier Amatriain & Jianfeng Gao, *Large Language Models: A Survey 1–2* (Mar. 23, 2025) (arXiv manuscript), <https://arxiv.org/abs/2402.06196v3> [<https://perma.cc/565Z-M4DF>] (providing a technical overview of LLMs and surveying the current research landscape).

³⁸ See Maxime Cohen, Tim Spittle & Jimmy Royer, *Assessing Algorithmic Versus Generative AI Pricing Tools*, LAW360 (Sep. 16, 2024, at 18:47 ET), <https://www.law360.com/articles/1879101/assessing-algorithmic-versus-generative-ai-pricing-tools> [<https://perma.cc/3XZR-HNM7>] (comparing the utility of large language models and traditional algorithm tools in the pricing context); see also Fish, Gonczarowski & Shorrer, *supra* note 17, at 3 (finding LLMs to be adept at pricing tasks).

³⁹ See OECD, *Algorithms and Collusion*, *supra* note 10, at 31–32 (describing the effect of “black box” models, which can deliver an optimal output “without revealing the relevant features that were behind the decision process,” making it increasingly difficult to interpret models and use traditional antitrust tools).

⁴⁰ See *id.*

machine learning models remain unreliable and often require significant expenditures in computing power.⁴¹

B. Defining “Competition”: Antitrust and Economic Theory

Under the microeconomic theory that underpins most of modern antitrust doctrine, markets function on a spectrum from competitive to oligopolistic to monopolistic. Idealized competitive markets are characterized by (among other things) low barriers to entry and perfect information between rational buyers and rationally profit-maximizing sellers, allowing many producers and consumers to fluidly exchange goods and services to the satisfaction of all participants.⁴² A perfectly competitive market maximizes consumer welfare: As producers must minimize prices or face displacement by new entrants, consumers pay the lowest prices possible while having full access to the quantity and range of goods desired.⁴³ In the real world, various imperfections like information asymmetries, transaction costs, and concentrating network effects disrupt this ideal state, leading to more uneven market structures and opening up opportunities and incentives for firms to gain market advantage.⁴⁴ Under this model, the concentration of market power in the hands of a few firms—oligopoly—tends to drive up prices, reduce competitive innovation, and negatively affect overall consumer welfare.⁴⁵

Antitrust law targets conduct that disrupts the incentive structures that enable rational, consumer-beneficial competition, with collusion as the classic example of anticompetitive behavior. *Economic collusion* occurs when rival firms exert market power together to raise prices above competitive levels by adhering to a common policy.⁴⁶ Collusive schemes are sustained by both the reward of supracompetitive profits for those who comply with the policy and the implicit threat of punishment—such

⁴¹ See, e.g., Haiyan Zhao, Hanjie Chen, Fan Yang, Ninghao Liu, Huiqi Deng, Hengyi Cai, Shuaiqiang Wang, Dawei Yin & Mengnan Du, *Explainability for Large Language Models: A Survey*, 15 ACM TRANSACTIONS ON INTELLIGENT SYS. & TECH. 1, 2, 5–10 (2024) (describing explainability techniques for large language models); George A. Vouros, *Explainable Deep Reinforcement Learning: State of the Art and Challenges*, 55 ACM COMPUTING SURVS., no. 92, 2023, at 1, 13–21 (describing recent explainability techniques for deep reinforcement learning models).

⁴² See AREEDA ET AL., *supra* note 7, at 4–6 (describing perfect competition). See generally Crane, *supra* note 18, at 1192–99 (describing some of the theoretical pillars of modern economic and antitrust theory).

⁴³ See, e.g., Crane, *supra* note 18, at 1196 (“Competition drives producers to design and make things that consumers value and to offer them at low prices.”).

⁴⁴ See AREEDA ET AL., *supra* note 7, at 7–9, 15–19 (describing various market imperfections).

⁴⁵ See Crane, *supra* note 18, at 1194–98 (explaining how the modern antitrust system is premised on a commitment to competitive markets).

⁴⁶ See OECD, *Algorithms and Collusion*, *supra* note 10, at 19.

as aggressive price undercutting or market exclusion—for those who deviate.⁴⁷ While *legal collusion*, constrained by the language of the Sherman Act, requires not only a common policy but also evidence of an agreement to trigger antitrust liability, in this Note, I use the term “collusion” to refer to economic collusion in order to describe this genre of competitively harmful collusive conduct more broadly. Collusion thus covers both unlawful arrangements achieved by agreement (i.e., cartels) as well as lawful “tacit collusion,” where a common policy is achieved through independent, though mutually interdependent, action.⁴⁸

Importantly, behavior that results in high prices merely based on responsiveness to competitors or demand conditions is not necessarily collusion. Collusion requires a “self-enforcing contract”: Each firm must find commitment to the common policy and punishment of defection to be in its own self-interest, because it believes that other firms have adopted the same policy.⁴⁹ Traditionally, economists view collusive arrangements—particularly those built on tacit understandings—as a delicate balancing act: Participants must be able to track and quickly respond to changes in others’ prices and output in order to maintain the common policy and punish defectors. Thus, collusion is considered more likely in highly concentrated, stable markets with few participants and minimal product variation or pricing complexity—in other words, markets where the amount of information to track is kept to a manageable level.⁵⁰

C. Theorized Algorithmic Impacts on the Market

Due to the difficulty of collecting high-quality data about pricing and business strategies in complex markets, real-world studies of pricing

⁴⁷ See Harrington, Jr., *Developing Competition Law*, *supra* note 15, at 334–36 (“Collusion ties future rewards and punishments to current behavior and that is what sustains a supracompetitive outcome. It is this causal relationship that links a firm’s current conduct with rival firms’ future conduct that defines collusion, not the setting of supracompetitive prices [itself].”).

⁴⁸ See generally Organisation for Economic Co-operation and Development [OECD] Comm. on Competition L. & Pol’y, *Mini-Roundtable on Oligopoly – Note by the US Department of Justice and the US Federal Trade Commission*, at 4–5, OECD Doc. DAF/FE/CLP/WD(99)13 (May 3, 1999) [hereinafter *U.S. Submission on Oligopoly*], <https://www.ftc.gov/sites/default/files/attachments/us-submissions-oecd-and-other-international-competition-fora/1999--Mini-Roundtable%20on%20Oligopoly.pdf> [<https://perma.cc/MVK4-8ZL2>] (noting that mere “conscious parallelism” and “interdependent behavior” are not actionable under Section 1 of the Sherman Act). See also *supra* notes 14–16 and accompanying text (discussing the Sherman Act and tacit collusion).

⁴⁹ See *U.S. Submission on Oligopoly*, *supra* note 48, at 4–5.

⁵⁰ See Michal S. Gal, *Algorithms as Illegal Agreements*, 34 BERKELEY TECH. L.J. 67, 74–75 (2019) (identifying market structure, product variation, market transparency, the predictability of demand, and the individual strategies and “personalit[ies]” of firms as five factors affecting the likelihood of collusive conduct).

algorithms are scarce, and most analyses of their potential competitive effects remain relatively abstract.⁵¹ The clearest starting point lies in the ability of computer systems to drastically reduce the costs of large-scale information management, enabling firms to process superhuman quantities of information, implement complex plans, and execute actions at speed. Algorithms make it radically cheaper to observe and interpret market conditions and consumer demand, and thus to make pricing decisions, especially in complex or rapidly fluctuating environments.⁵² They can be used to segment demand and surface the most relevant products to consumers on an individual level, lowering advertising costs and enabling market entry.⁵³ In theory, the high-volume information processing, frequent price changes, and rational decisionmaking enabled by computer systems can contribute to better price discovery and thus overall market efficiency.⁵⁴ Some empirical studies have demonstrated these effects, suggesting that algorithmic pricing systems can contribute to overall welfare.⁵⁵

On the other hand, because algorithmic systems make information management so much easier, many legal and economic scholars view them as critical facilitators of collusive conduct. Because of the high costs of technological development and the network effects produced

⁵¹ I discuss the leading empirical studies on the competitive effects of algorithmic pricing later in this Note, but for some examples, see Sophie Calder-Wang & Gi Heung Kim, *Algorithmic Pricing in Multifamily Rentals: Efficiency Gains or Price Coordination?* 1 (Aug. 16, 2024) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4403058 [<https://perma.cc/Z3NH-9BX4>] (finding higher demand responsiveness in markets with greater use of algorithmic pricing); Le Chen, Alan Mislove & Christo Wilson, *An Empirical Analysis of Algorithmic Pricing on Amazon Marketplace*, 2016 PROC. 25TH INT'L CONF. ON WORLD WIDE WEB 1339, 1348 (2016) (finding that algorithmic sellers are generally more successful than non-algorithmic sellers, winning Amazon's "Buy Box" more frequently even when not the lowest price); Hanspach, Sapi & Wieting, *supra* note 20 (finding little to no evidence of collusive pricing in a study of Dutch e-commerce platform Bol.com and finding algorithmic pricing in monopoly markets to be associated with lower prices than human-set prices in the same); Ioannis Stamatopoulos, Naveed Chehrazi & Achal Bassamboo, *Welfare Implications of Inventory-Driven Dynamic Pricing*, 65 MGMT. SCI. 5741, 5741–43 (2019) (finding operational efficiencies without overall consumer harms in a study of inventory cost-based dynamic pricing in brick and mortar retailers).

⁵² See Nazzini & Henderson, *supra* note 22, at 2–3 (explaining that automated pricing makes it easier for sellers to adapt to rapid market changes); Francisco Beneke & Mark-Oliver Mackenrodt, *Remedies for Algorithmic Tacit Collusion*, 9 J. ANTITRUST ENF'T 152, 161 (2020) (“[O]ne evident benefit from this technology is lower costs of making optimal price predictions.”).

⁵³ See Beneke & Mackenrodt, *supra* note 52, at 161 (explaining how pricing algorithms help in segmenting demand and identifying customers); Gina-Gail S. Fletcher, *Deterring Algorithmic Manipulation*, 74 VAND. L. REV. 259, 262 (2021) (discussing benefits of algorithmic trading in capital markets).

⁵⁴ See Nazzini & Henderson, *supra* note 22, at 3; Fletcher, *supra* note 53, at 262.

⁵⁵ See *supra* note 51.

by online platforms, markets with widespread use of algorithmic systems may naturally tend towards higher concentration to start.⁵⁶ Price transparency in online markets allows sellers to better monitor rivals' activities, enabling faster detection and punishment of defection and the maintenance of complex collusive policies across far more products.⁵⁷ Firms armed with large-scale data processing capabilities are also better able to monitor and tailor their prices to demand conditions, allowing cartels to distinguish true defections from exogenous demand shocks and thus reduce unnecessary price wars resulting from misunderstandings.⁵⁸ Finally, pricing algorithms are immune to human social and emotional dynamics, as they do not operate on social trust and do not react to emotional triggers; firms that delegate pricing decisions to algorithms might be better at resisting the temptation to deviate from rationally beneficial collusive arrangements.⁵⁹

Most economic studies demonstrating collusive behavior by pricing algorithms have been simulation experiments of highly stylized markets, often involving algorithms programmed with simple profit-maximization objectives. A number of studies pitting reinforcement learning models against each other in simulated oligopoly markets have found that these models can consistently fall into and maintain collusive reward-punishment schemes, resulting in supracompetitive prices.⁶⁰ However, researchers have also noted that results can vary widely depending on the specific assumptions made in market and

⁵⁶ See Michael L. Katz & Carl Shapiro, *Systems Competition and Network Effects*, 8 J. ECON. PERSPS. 93, 112 (1994) (“[D]ue to economies of scale and product differentiation, [systems] markets are often characterized by oligopoly or monopolistic competition, not perfect competition.”).

⁵⁷ See Beneke & Mackenrodt, *supra* note 52, at 162–63; see also Winston Wei Dou, Itay Goldstein & Yan Ji, *AI-Powered Trading, Algorithmic Collusion, and Price Efficiency 5* (Jan. 27, 2024) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4452704 [<https://perma.cc/N83X-EZN3>] (discussing a “paradoxical situation concerning price informativeness” in capital markets, in which high price informativeness facilitates collusion, which in turn compromises price informativeness).

⁵⁸ See Jason O'Connor & Nathan E. Wilson, *Reduced Demand Uncertainty and the Sustainability of Collusion: How AI Could Affect Competition*, 54 INFO. ECON. & POL'Y, no. 100882, 2021, at 1, 2 (discussing the impacts of reduced demand uncertainty).

⁵⁹ See *id.*; Salil K. Mehra, *Antitrust and the Robo-Seller: Competition in the Time of Algorithms*, 100 MINN. L. REV. 1323, 1328–29 (2016) (noting that algorithmic sellers “solve” the issues of humans’ hyperbolic discount rates and irrational tendencies, lessening the chance of impatient or mistaken defection).

⁶⁰ See, e.g., Calvano et al., *Artificial Intelligence*, *supra* note 30, at 30 (simulating repeated price competition in various oligopoly structures); Timo Klein, *Autonomous Algorithmic Collusion: Q-Learning Under Sequential Pricing*, 52 RAND J. ECON. 538, 538 (2021) (simulating repeated competition in duopoly model); Justin P. Johnson, Andrew Rhodes & Matthijs Wildenbeest, *Platform Design When Sellers Use Pricing Algorithms*, 91 ECONOMETRICA 1841, 1843 (2023) (using Q-learning algorithms to simulate the effect of platform-level demand-steering rules).

algorithm design,⁶¹ and with limited empirical evidence of what designs are actually being used in real markets, it's difficult to assess whether the predicted collusive behavior of these algorithms poses a real-world threat.

Whether pricing algorithms actually facilitate collusion in real markets remains ambiguous, especially when considering the range of variations in firm behavior and market structure that can't be effectively simulated. For example, the same access to information about market conditions and competitor behavior that enables fast punishment might also incentivize defection and thereby destabilize collusive agreements, given that firms can more optimally time deviations to maximize short-term profits.⁶² Firm-by-firm variations in such aspects as pricing technology, marketing strategy, inventory management, and managerial style can lead to variations in update speeds, and thus an inability to maintain a single collusive price.⁶³ Algorithm-enabled, increasingly granular price discrimination can make market and competitor observations more costly and fragment the market to the benefit of defectors and new entrants. Given the complexity and diversity of these systems and the markets in which they operate, it's no surprise that approaches attempting to predict their behavior based on theoretical principles alone have produced little clarity.

II

BLUNT TOOLS: LIMITATIONS OF ANTITRUST-BASED REGULATION OF ALGORITHMS

Because of the longstanding, theory-first assumption that algorithmic systems primarily cause harm by facilitating collusive conduct, lawyers have gravitated towards antitrust as an organizing framework for regulation. Academics, regulators, and policymakers alike have fixated on a set of classically thorny issues in antitrust law—the rationales behind the agreement requirement, the assignment of liability to nonhuman entities, even the pleading standard—with the hope of extending the bounds of antitrust to address new forms of collusion. But these antitrust-focused approaches are too narrow, succeeding primarily where algorithms play only an incidental role

⁶¹ See Asker, Fershtman & Pakes, *supra* note 30, at 6 (finding that reinforcement learning algorithms can produce near-monopoly prices when programmed to learn only from actions actually taken and competitive prices when programmed to conduct internal counterfactual experiments for each move).

⁶² See O'Connor & Wilson, *supra* note 58, at 2.

⁶³ See Zach Y. Brown & Alexander MacKay, *Competition in Pricing Algorithms*, 15 AM. ECON. J.: MICROECONOMICS 109, 118–20 (2023).

and otherwise failing to bridge the gap between academic innovations and policy in practice. In this Part, I describe leading legal theories of algorithmic pricing and competition and argue that a critical gap exists between the speculative scenarios contemplated by legal scholars and the far narrower scope of issues that have been addressed in real regulatory policy.

A. *Prevailing Legal Theories of Algorithmic Coordination*

Since legal theory centers on conduct attributable to discrete actors who can bear liability for potential harms, legal academic scholarship tends to ascribe to algorithms a humanlike quality of agency. As then-FTC acting chairwoman Maureen K. Ohlhausen argued in 2017, algorithms can easily be viewed as intermediaries, subject to the normal laws of causation, fault, and agency: “Everywhere the word ‘algorithm’ appears, please just insert the words ‘a guy named Bob.’ . . . If it isn’t ok[ay] for a guy named Bob to do it, then it probably isn’t ok[ay] for an algorithm to do it either.”⁶⁴ Much of the legal scholarship on algorithmic pricing has tended toward a similar view of algorithms as agent-like actors, subject to the same rational behavioral principles as humans underneath a thin veneer of computerized abstraction.⁶⁵ These views have only gained traction with the rise of advanced conversational artificial intelligence systems like LLMs, with some academics now advocating for respondeat superior liability for algorithmic action, and even for theories of algorithmic criminal intent.⁶⁶

Most analyses of algorithmic pricing in terms of traditional anticompetitive conduct are covered by a four-part framework put forth in 2016 by Ariel Ezrachi, a professor of competition law at the University of Oxford, and Maurice Stucke, a former DOJ antitrust attorney and current professor of law at the University of Tennessee.

⁶⁴ Maureen K. Ohlhausen, Acting Chairman, U.S. Fed. Trade Comm’n, *Should We Fear the Things that Go Beep in the Night? Some Initial Thoughts on the Intersection of Antitrust Law and Algorithmic Pricing* (May 23, 2017), https://www.ftc.gov/system/files/documents/public_statements/1220893/ohlhausen_-_concurrences_5-23-17.pdf [<https://perma.cc/EK82-CGTX>] (quoting Ohlhausen’s “guy named Bob” speech); *see also In re RealPage, Inc., Rental Software Antitrust Litig.* (No. II), 709 F. Supp. 3d 478, 511–12 (M.D. Tenn. 2023) (order denying dismissal of certain plaintiffs’ complaints and granting dismissal of other plaintiffs’ complaints).

⁶⁵ *See, e.g.,* Fish, Gonczarowski & Shorrer, *supra* note 17, at 2, 22–23 (referring to LLMs as “a completely new kind of economic agent, worthy of separate behavioral analysis” and analyzing the “reasoning” processes of these models); Beneke & Mackenrodt, *supra* note 52, at 162 (claiming that algorithms “can . . . be more rational than humans”); Michal S. Gal, *Limiting Algorithmic Coordination*, 38 BERKELEY TECH. L.J. 173, 188 (2023) (concluding that the simulated algorithms in Calvano et al., *Artificial Intelligence*, *supra* note 30, behaved in a manner “very much consistent with . . . coordination between rational agents”).

⁶⁶ *See, e.g.,* Asil & Wollmann, *supra* note 17, at 29, 36.

Ezrachi and Stucke proposed a set of four anticompetitive scenarios involving algorithms: the “messenger,” where algorithms are used to effectuate explicit human-planned cartels; the “hub and spoke,” where a single algorithm is used to coordinate the activities of many competitors; the “predictable agent,” where firms independently deploy algorithms programmed to react collusively to competitors’ prices; and the “digital eye,” where fully autonomous, nearly omniscient algorithmic agents reach collusive arrangements entirely on their own.⁶⁷ Their framing of algorithmic pricing problems has been highly influential over the last decade, shaping analyses and commentary by international trade organizations,⁶⁸ U.S. and European regulators,⁶⁹ numerous legal scholars,⁷⁰ and general-audience publications like *The New Yorker*.⁷¹

In this framework, rooted in antitrust theory and the legal tendency to focus on actors who can bear liability, anticompetitive conduct can be attributed to humans, computers, or both. The “messenger” and “hub and spoke” scenarios are straightforward twists on classic cartels. The “predictable agent” attributes anticompetitive intent to the agent’s human designers but also injects an element of computer agency, as the authors describe “algorithms reaching a similar common understanding” and “machines which are aware” of interdependent

⁶⁷ See ARIEL EZRACHI & MAURICE E. STUCKE, VIRTUAL COMPETITION: THE PROMISE AND PERILS OF THE ALGORITHM-DRIVEN ECONOMY 35–81 (2016) [hereinafter EZRACHI & STUCKE, VIRTUAL COMPETITION]; see also Ariel Ezrachi & Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition*, 2017 U. ILL. L. REV. 1175, 1782–84 (2017) [hereinafter Ezrachi & Stucke, *Artificial Intelligence & Collusion*] (reiterating framework).

⁶⁸ See, e.g., OECD, *Algorithms and Collusion*, *supra* note 10, at 11–12, 22, 28, 39–42, 50 (citing works by Ezrachi and Stucke throughout).

⁶⁹ See, e.g., McSweeney & O’Dea, *supra* note 12, at 75–76 (referencing the “messenger” and “predictable agent” scenarios); Competition & Mkts. Auth., *Pricing Algorithms: Economic Working Paper on the Use of Algorithms to Facilitate Collusion and Personalised Pricing* 4–5 (CMA Working Paper, Paper No. CMA94, 2018), https://assets.publishing.service.gov.uk/media/5bbb2384ed915d238f9cc2e7/Algorithms_econ_report.pdf [<https://perma.cc/3EY4-R3SV>] (presenting Ezrachi and Stucke’s scenarios as three major “theories of harm” from pricing algorithms).

⁷⁰ See, e.g., Klein, *supra* note 60, at 540 (crediting Ezrachi and Stucke, as well as Mehra, *supra* note 59, for “[t]he inception of the academic debate around pricing algorithms and collusion”); Alexander MacKay & Samuel N. Weinstein, *Dynamic Pricing Algorithms, Consumer Harm, and Regulatory Response*, 100 WASH. U. L. REV. 111, 129–30 (2022) (discussing the “messenger” and “hub-and-spoke” scenarios as part of the “scholarly consensus” on algorithmic facilitation of price collusion); Crane, *supra* note 18, at 1126 (arguing that “[t]he digital eye is no longer a farfetched idea” and that algorithms are quickly “leapfrogging” antitrust doctrine altogether); Harrington, Jr., *Developing Competition Law*, *supra* note 15, at 333, 357 (citing Ezrachi and Stucke for “[e]arly contributions” to algorithmic collusion research).

⁷¹ See Jill Priluck, *When Bots Collude*, NEW YORKER (Apr. 25, 2015), <https://www.newyorker.com/business/currency/when-bots-collude> [<https://perma.cc/WE93-DVWV>] (discussing the “predictable agent” scenario).

markets.⁷² And in the “digital eye” scenario, machines operate with total autonomy, behaving anticompetitively entirely on their own.⁷³ Each scenario contains a clear and compelling antitrust question: Is there an agreement reachable by the law? For Ezechia and Stucke, in the “predictable agent” and “digital eye” scenarios, the answer is no—both situations are clear-cut tacit collusion beyond the reach of antitrust⁷⁴—and the job of regulators is to figure out how to adapt.⁷⁵

Critical discussion of this “established taxonomy”⁷⁶ by other legal scholars tends to buy into the baseline emphasis on conduct and attribution. One academic attempt to reorganize this framework divided the scenarios into two categories—“human-relatable conduct” and “purely automated conduct”—based on the element of human agreement required for liability under antitrust law.⁷⁷ The authors found Ezechia and Stucke’s categories underinclusive for the purposes of conduct attribution: For example, the “hub and spoke” scenario, under a liability-based framework, would properly encompass the use of not only pricing platforms but also common data pools and human third-party pricing consultants.⁷⁸ Likewise, a 2018 analysis by U.K. competition authorities analyzed the four categories in terms of regulators’ ability to impose liability under antitrust law, focusing on tacit collusion problems in the latter three scenarios and finding the “hub and spoke” scenario to present “the most immediate risk” in practice.⁷⁹ The “predictable agent” and “digital eye” were deemed only possible “in principle,” dependent on further technological advancement and the popularization of algorithmic pricing.⁸⁰ Despite these attempts at analysis, little has been said as to how each scenario should actually work in real-world practice.

Across legal scholarship, the fundamental assumption behind Ezechia and Stucke’s four scenarios—that the core risk of algorithmic pricing is that more technologically advanced algorithms will behave, and thus collude, like rational agents—is rarely questioned. Analyses premised on this assumption tend to ignore structural factors unrelated

⁷² Ezechia & Stucke, *Artificial Intelligence & Collusion*, *supra* note 67, at 1789–91.

⁷³ *Id.* at 1783–84.

⁷⁴ Ezechia & Stucke, *Algorithmic Tacit Collusion*, *supra* note 16, at 220–22.

⁷⁵ *See id.* at 220, 257–59 (discussing suggestions for regulators to better understand algorithmic tacit collusion).

⁷⁶ Nazzini & Henderson, *supra* note 22, at 5.

⁷⁷ *Id.* at 6–13 (identifying a technical taxonomy dividing between rule-based and machine learning systems, and a legal taxonomy building on Ezechia and Stucke’s work, distinguishing human-relatable from purely automated categories of conduct).

⁷⁸ *Id.* at 11.

⁷⁹ Competition & Mkts. Auth., *supra* note 69, at 4–5.

⁸⁰ *Id.*

to algorithmic autonomy, such as market relationships between firms, firms' access to public and private data, and technical differences between pricing algorithms. Perhaps as a consequence, few concrete studies of these four scenarios have emerged. As I discuss in Part III, however, an explosion of empirical and theoretical research in the last few years⁸¹ has demonstrated that pricing harms can issue from a much wider variety of algorithmic interactions than contemplated under an antitrust-focused framework.

B. *Antitrust Litigation and Its Limits*

While legal academics discuss remedies for autonomously colluding algorithmic agents, actual antitrust enforcement has been confined to conventional fact patterns involving human-led agreements with evidence of intent, perhaps showing regulators' reluctance to pursue unproven doctrinal hypotheticals under judicial scrutiny. Much fanfare and anticipation followed *United States v. Topkins*, a 2015 DOJ prosecution of a human-led conspiracy to fix the price of posters sold on Amazon via simple algorithms⁸²: an unsophisticated “messenger” case.⁸³ Yet despite the limited use of algorithms in *Topkins*, this “small-stakes case” with “one foot in the old cartel world”⁸⁴ remained the only major U.S. antitrust litigation targeting algorithmic pricing harms until *RealPage* and a wave of related suits, all alleging similar hub-and-spoke schemes using pricing platforms to raise prices in rental housing and hotel markets.⁸⁵ All signs suggest that *RealPage*-style claims against third-party pricing providers may become a new mainstream litigation opportunity, as private civil suits against *RealPage* and competing rental pricing service *Yardi* have now developed into large multidistrict

⁸¹ See *infra* Section III.A.

⁸² See Plea Agreement at 3–4, *United States v. Topkins*, No. 3:15-CR-00201-WHO (N.D. Cal. Apr. 30, 2015) [hereinafter *Topkins* Plea Agreement]; see also Ezrachi & Stucke, *Artificial Intelligence & Collusion*, *supra* note 67, at 1777, 1809 (discussing noteworthiness of *Topkins* case); McSweeney & O’Dea, *supra* note 12, at 75 (analyzing *Topkins*); Priluck, *supra* note 71 (opening general-readership magazine article with discussion of *Topkins*).

⁸³ See *supra* notes 67–72 and accompanying text (discussing “messenger” scenario). In *Topkins*, the defendant engaged in explicit discussions with co-conspirators to use specific simple algorithms to coordinate price changes. As in the “messenger” scenario, algorithms played no part in the actual decision-making or information-sharing processes necessary to maintain the conspiracy. See *Topkins* Plea Agreement, *supra* note 82, at 3–4.

⁸⁴ Ezrachi & Stucke, *Artificial Intelligence & Collusion*, *supra* note 67, at 1809.

⁸⁵ See *In re RealPage, Inc., Rental Software Antitrust Litig. (No. II)*, No. 3:23-MD-3071 (M.D. Tenn. consolidated Apr. 12, 2023); *Duffy v. Yardi Sys., Inc.*, No. 2:23-cv-01391 (W.D. Wash. filed Sep. 8, 2023); *Gibson v. CENDYN Group, LLC*, No. 2:23-cv-00140 (D. Nev. filed Jan. 25, 2023); *Cornish-Adebiyi v. Caesars Entertainment, Inc.*, No. 1:23-cv-02536 (D.N.J. filed May 9, 2023); *Dai v. SAS Institute, Inc.*, No. 4:24-cv-02537 (N.D. Cal. filed Apr. 26, 2024); *United States v. RealPage, Inc.*, No. 1:24-cv-00710 (M.D.N.C. filed Aug. 23, 2024).

litigations surviving past the dismissal stage.⁸⁶ And in late 2024, two medical associations began private litigation against MultiPlan, a pricing service for medical insurers, alleging that MultiPlan used proprietary claim and reimbursement data from insurers to coordinate and artificially depress reimbursement rates.⁸⁷

Though *RealPage* has drawn significant attention as a leading example of algorithmic pricing harms, the core factual elements of the case—and others like it, including *Yardi* and *MultiPlan*—remain firmly rooted in traditional theories of collusive conduct. All of these cases involve substantially similar claims: in *RealPage* and *Yardi*, that pricing recommendation platforms orchestrated a scheme among landlords to inflate rents based on centralized algorithmic recommendations; and in *MultiPlan*, that an insurance pricing service did the same with insurers to collectively decrease reimbursement rates paid out to medical providers.⁸⁸ The aforementioned three cases, which have all survived motions to dismiss, involve the alleged exchange of competitively sensitive price information, which courts have recognized as a “well-settled” indicator of anticompetitive agreement since long before the rise of algorithmic systems.⁸⁹ In *RealPage* and *Yardi*, that information exchange occurred when landlords allegedly submitted their private pricing and leasing data for use in training RealPage and Yardi’s machine learning models, raising novel issues of whether sensitive data can be “shared” even

⁸⁶ See *In re RealPage, Inc., Rental Software Antitrust Litig.* (No. II), 709 F. Supp. 3d 478, 478, 492 (M.D. Tenn. 2023) (granting dismissal in part and denying dismissal in part); *Duffy v. Yardi Sys., Inc.*, 758 F. Supp. 3d 1283, 1297–98 (W.D. Wash. 2024) (denying defendants’ motion to dismiss). One state court case brought against Yardi under California’s state antitrust law was later defeated at summary judgment, upon plaintiffs’ failure to prove from Yardi’s disclosed source code that any confidential information was actually shared between landlords. See *Mach v. Yardi Sys., Inc.*, No. 24CV063117, slip op. at 2 (Cal. Super. Ct. Oct. 6, 2025).

⁸⁷ See Complaint at 5–6, *Am. Med. Ass’n v. MultiPlan, Inc.*, No. 1:24-cv-10959 (N.D. Ill. Oct. 24, 2024) [hereinafter *MultiPlan* Complaint]. Litigation against MultiPlan has now been consolidated into multidistrict litigation covering both a class action and a direct action complaint. Consolidated Master Direct Action Plaintiff Complaint at 1, *In re MultiPlan Health Ins. Provider Litig.*, No. 1:24-cv-06795 (N.D. Ill. filed Nov. 18, 2024); Consolidated Class Action Complaint at 1, *In re MultiPlan Health Ins. Provider Litig.*, No. 1:24-cv-06795 (N.D. Ill. filed Nov. 18, 2024).

⁸⁸ See *U.S. v. RealPage Amended Complaint*, *supra* note 6, at 1–5 (presenting claims against RealPage); *Yardi*, 758 F. Supp. 3d at 1292–93, 1298 (denying Yardi’s motion to dismiss); *MultiPlan* Complaint, *supra* note 87, at 1–8 (presenting claims against MultiPlan).

⁸⁹ *In re MultiPlan Health Ins. Provider Litig.*, 789 F. Supp. 3d 614, 641 (N.D. Ill. 2025) (order granting dismissal in part and denying dismissal in part) (quoting *In re Broiler Chicken Antitrust Litig.*, No. 1:16-cv-08637, 2025 WL 461407, at *4 (N.D. Ill. Feb. 11, 2025)); *cf. In re Pork Antitrust Litig.*, 781 F. Supp. 3d 758, 800 (D. Minn. 2025) (order granting summary judgment in part and denying summary judgment in part) (noting that pricing information exchanges are “not per se unlawful,” requiring further analysis under the rule of reason).

after aggregation and transformation in a machine learning system.⁹⁰ But in *MultiPlan*, even where plaintiffs failed to claim the use of private data in the pricing algorithm, the court found that allegations of MultiPlan's human-led business communications with insurers alone involved enough sensitive information exchange to sustain an inference of unlawful agreement—suggesting that these cases are less about algorithms than might initially appear.⁹¹ Meanwhile, other cases failing to plausibly allege or prove private information exchange have largely been shut down; courts have generally declined to find antitrust-actionable harms resulting from the mere use of complex price-setting algorithms.⁹²

A recurring theme throughout these cases has been an underlying assumption that pricing algorithms are only regulable by antitrust insofar as they take the obvious place of legal actors who would be held legally accountable in the same situation. Both the *RealPage* and *Yardi* courts cited former FTC acting chair Ohlhausen's "guy named Bob" metaphor in finding a plausibly alleged illegal agreement, analogizing the pricing services at issue to a "common, outside agent" or intermediary.⁹³ Those cases, like *MultiPlan*, appear to hinge on clear allegations of explicit contracts or communications to exchange private information.⁹⁴ By contrast, in a similar case involving hotel room pricing, the court firmly

⁹⁰ See *In re RealPage*, 709 F. Supp. 3d at 503 ("As part of the written contract, each Defendant allowed RealPage to use its proprietary commercial data as an input to its [pricing] software . . ."); *Yardi*, 758 F. Supp. 3d at 1293–94 (discussing landlord defendants' "use[of] an intermediary, Yardi, to compile their commercially sensitive data"). But see *Mach*, slip op. at 7 (finding after discovery that plaintiffs could not prove that Yardi's pricing recommendation tools shared confidential information between landlords).

⁹¹ See *In re MultiPlan*, 789 F. Supp. 3d at 641 (finding that "the crux of the plaintiffs' information-sharing allegations goes beyond MultiPlan's algorithm").

⁹² See, e.g., *Gibson v. CENDYN Grp., LLC*, No. 2:23-CV-00140, 2024 WL 2060260, at *1, *4 (D. Nev. May 8, 2024), *aff'd*, 148 F.4th 1069 (9th Cir. 2025) (dismissing case with prejudice based on lack of alleged private data sharing); *Cornish-Adebiyi v. Caesars Ent., Inc.*, No. 1:23-CV-02536, 2024 WL 4356188, at *5, *7, n.6 (D.N.J. Sep. 30, 2024) (same); *Mach*, No. 24-CV-063117, slip op. at 2, 10 ("[A]dopting a common software application itself is not an antitrust violation.").

⁹³ *In re RealPage*, 709 F. Supp. 3d at 512, 518; *Yardi*, 758 F. Supp. 3d at 1293.

⁹⁴ See *In re RealPage*, 709 F. Supp. 3d at 510 ("[The complaint's] most persuasive evidence of horizontal agreement is the simple undisputed fact that each [landlord] defendant provided RealPage its proprietary commercial data, knowing that RealPage would require the same from its horizontal competitors and use all of that data to recommend rental prices to its competitors."); *Yardi*, 758 F. Supp. 3d at 1295 ("[T]he key to plaintiffs' antitrust claims is the horizontal agreements between and among the lessor defendants to entrust Yardi with their sensitive commercial information in order to obtain and implement the supracompetitive rental rates generated by Yardi's algorithm."). But see *Mach*, No. 24CV063117, slip op. at 6–7 (finding no evidence after discovery that landlords' contracts with Yardi provided for an exchange of information for price-setting and that, in fact, Yardi obtained some commercially sensitive information from landlords by surreptitious means).

rejected plaintiffs' allegations of indirect information exchange through the training of a machine learning model without concrete evidence of human agreement.⁹⁵ There, the court compared the algorithm at issue to an attorney who improves her skills using each client's confidential information but who never actually agrees to share that information between clients.⁹⁶ But these analogies say more about lawyers' tendency to shoehorn algorithmic behavior into existing conduct frameworks than about how these systems might actually cause harm. Without further investigation into the actual dynamics of pricing algorithms in real markets, innovation in antitrust regulation seems unlikely.

C. *Constrained Experimentation in the Legislature*

Legislative efforts to regulate algorithmic pricing in the wake of *RealPage* have generally narrowly focused on adjustments to antitrust doctrine, though experiments with more expansive prohibitions are taking place in some states and on the municipal level. Two Senate bills first introduced in 2024, proposing direct changes to the Section 1 legal standard, have served as templates for a flurry of state and local proposals over the last two years intended to address *RealPage*-like harms.⁹⁷ The Preventing Algorithmic Collusion Act ("Algorithmic Collusion Act"), which generally prohibits pricing algorithms that use private competitor data, would create an automatic presumption of unlawful agreement under Section 1 for the distribution and use of such algorithms.⁹⁸ Several state bills, including those passed in New York and considered in Colorado, create similar shortcuts to the finding of unlawful agreement under state antitrust laws for the

⁹⁵ See *Gibson*, 2024 WL 2060260, at *5–6.

⁹⁶ *Id.* at 9.

⁹⁷ See, e.g., N.Y. GEN. BUS. LAW § 340-B (added by S.B. S7882, effective Dec. 15, 2025) (barring the use of algorithmic price recommendation software in rental housing); CAL. BUS. & PROF. CODE §§ 16729, 16756.1 (added by A.B. 325, effective Jan. 1, 2026) (prohibiting the use of pricing algorithms in coercion and in conspiracies to restrain trade); 2025 Conn. Acts 25-1 (Nov. Spec. Sess.) (added by H.B. 8002, effective Jan. 1, 2026) (barring the use of rental pricing recommendation services using nonpublic competitor data); H.B. 1427, 104th Gen. Assemb. (Ill. 2025) (same); H.B. 25-1004, 75th Gen. Assemb., 1st Reg. Sess. (Colo. 2025) (vetoed May 29, 2025) (barring the use of algorithmic pricing in rental housing and reducing the state antitrust pleading standard for plaintiffs); BERKELEY, CALIF., MUN. CODE ch. 13.63 (2025) (effective Mar. 1, 2026) (prohibiting the use and sale of any rental pricing recommendation algorithm using all competitor data); MINNEAPOLIS, MINN., CODE OF ORDINANCES § 244.2070 (2025) (effective Mar. 1, 2026) (barring the use of rental pricing algorithms using nonpublic data).

⁹⁸ Preventing Algorithmic Collusion Act of 2024, S. 3686, 118th Cong. § 5(a) (as referred to S. Comm. on the Judiciary, Jan. 30, 2024). After failing to pass in the last Senate session, this bill was reintroduced in early 2025. Preventing Algorithmic Collusion Act of 2025, S. 232, 119th Cong. (as referred to S. Comm. on the Judiciary, Jan. 23, 2025).

use of pricing recommendation algorithms in the rental housing context.⁹⁹ The second Senate bill, the Preventing the Algorithmic Facilitation of Rental Housing Cartels Act (“Rental Housing Cartels Act”), specifically targets pricing recommendations in rental property and overrides the existing Section 1 pleading standard¹⁰⁰: It provides that a rental price-fixing complaint by federal or state enforcers need only allege “consciously parallel pricing coordination” and “need not allege facts tending to exclude the possibility of independent action.”¹⁰¹ California’s 2025 algorithmic pricing law contains matching language under the state’s antitrust statute, broadly softening the pleading standard for all complaints dealing with commercial pricing algorithms.¹⁰² Both of the above approaches clearly target the tacit collusion problem by reducing the burden on plaintiffs to allege or even prove an unlawful agreement.

State bills on pricing algorithms tend to roughly follow the antitrust-oriented blueprints set by the two Senate bills, often defining prohibited algorithmic services in terms of a “coordinating function” and typically focusing on the use of nonpublic data obtained from competitors.¹⁰³ Non-antitrust approaches are rare but have drawn interest: California’s recent law, for example, creates a new, non-antitrust basis for liability for algorithm providers who “coerce[]” users into adopting their price recommendations.¹⁰⁴

Perhaps counterintuitively, despite a general focus on specific elements of Section 1, most of these new legislative efforts are also remarkably blunt instruments, drastically altering legal standards to enable aggressive antitrust enforcement while rarely addressing the

⁹⁹ See N.Y. GEN. BUS. LAW § 340-B (2025) (considering the use of pricing recommendation software to set rental terms “an unlawful agreement”); H.B. 25-1004, 75th Gen. Assemb., 1st Reg. Sess. (Colo. 2025) (vetoed May 29, 2025) (considering the use of rental pricing algorithms “an illegal restraint of trade or commerce”).

¹⁰⁰ See *Bell Atlantic Corp. v. Twombly*, 550 U.S. 544, 554 (2007) (“[P]roof of a [Section 1] conspiracy must include evidence tending to exclude the possibility of independent action.”).

¹⁰¹ Preventing the Algorithmic Facilitation of Rental Housing Cartels Act of 2024, S. 3692, 118th Cong. § 4(a) (as referred to S. Comm. on the Judiciary, Jan. 30, 2024); see also Colo. H.B. 25-1004 § 3 (containing similar language).

¹⁰² See CAL. BUS. & PROF. CODE § 16756.1 (2025) (“[I]n a complaint for any violation of this chapter . . . the complaint shall not be required to allege facts tending to exclude the possibility of independent action.”).

¹⁰³ For examples, see *supra* note 97.

¹⁰⁴ See CAL. BUS. & PROF. CODE § 16729 (2025) (“It shall be unlawful for a person to use or distribute a common pricing algorithm if the person coerces another person to set or adopt a recommended price or commercial term”); see also Paul D. Brachman et al., *California Restricts Use of Common Pricing Algorithms*, PAUL, WEISS (Oct. 13, 2025), <https://www.paulweiss.com/insights/client-memos/california-restricts-use-of-common-pricing-algorithms> [<https://perma.cc/3TAA-ZHGV>] (analyzing CAL. BUS. & PROF. CODE §§ 16729, 16756.1).

specific mechanisms of harm. Bills like the Algorithmic Collusion Act, which automatically outlaw pricing algorithms using nonpublic competitor data,¹⁰⁵ could put gig economy platforms like Uber on shaky legal ground: At least one court has accepted a view of Uber's drivers as technically independent competitors who share data, like location and rating, with Uber in exchange for centralized pricing by Uber's algorithm.¹⁰⁶ Meanwhile, the Rental Housing Cartels Act and a new law passed in New York¹⁰⁷ broadly prohibit rental owners from using any price recommendation service using several types of property data—without any requirement that the data be private—and could easily be read to cover a variety of commonplace analytics and recommendation activities based on public information.¹⁰⁸ Such wide-sweeping legislation could open the courts to a flood of costly litigation—RealPage itself has already sued to enjoin New York and the city of Berkeley, California from enforcing their algorithmic pricing regulations on First Amendment grounds¹⁰⁹—and chill a substantial amount of legitimate and consumer-friendly innovation.

Nothing mandates that legislation addressing algorithmic pricing hew closely to antitrust scholars' preoccupation with tacit collusion and the Sherman Act's agreement requirement: Legislators are free to craft systemic regulations far beyond any individual legal doctrine. But lacking both deep empirical data and a coherent, fact-based framework

¹⁰⁵ See, e.g., S. 3686 § 5(a); CAL. BUS. & PROF. CODE § 16729 (2025); see also Brachman et al., *supra* note 104, at 3 (warning that California's new coercion provision "could reach a range of common incentive structures and commercial terms").

¹⁰⁶ See *Meyer v. Kalanick*, 174 F. Supp. 3d 817, 827–29 (S.D.N.Y. 2016) (denying dismissal of a price-fixing claim alleging a conspiracy between Uber and its drivers to restrict price competition).

¹⁰⁷ S. 3692 § 3(a); N.Y. GEN. BUS. LAW § 340-B (McKinney 2025).

¹⁰⁸ The Rental Housing Cartels Act declares a per se Sherman Act violation for any rental property owner or agent to contract for the services of any "coordinator," defined as "any person that operates a software or data analytics service that performs a coordinating function." S. 3692 §§ 2(5), 3(a)(1). A "coordinating function" is in turn defined as the collection and computational processing of "historical or contemporaneous prices, supply levels, or lease or rental contract termination and renewal dates of residential dwelling units from [two] or more rental property owners" combined with the provision of price, lease term, or occupancy recommendations. *Id.* § 2(4). The Act contains no language exempting recommendations based on processing of publicly available data. The New York law contains nearly identical language defining "coordinating function" and similarly contains no exemptions for public data. N.Y. GEN. BUS. LAW § 340-B (2025); see also Shylah R. Alfonso, Christopher A. Williams, Caroline G. Tunca & Robert C.S. Berry, *Algorithmic Price-Fixing: US States Hit Control-Alt-Delete on Digital Collusion*, PERKINS COIE (Dec. 30, 2025), <https://perkinscoie.com/insights/update/algorithmic-price-fixing-us-states-hit-control-alt-delete-digital-collusion> [<https://perma.cc/TC6U-FFP6>] (noting lack of public data exception in New York law).

¹⁰⁹ See *Complaint, RealPage, Inc. v. James*, No. 1:25-cv-9847 (S.D.N.Y. filed Nov. 26, 2025); *Complaint, RealPage, Inc. v. City of Berkeley*, No. 3:25-cv-03004 (N.D. Cal. filed Apr. 2, 2025).

for the full scope of algorithmic pricing harms, policymakers, like federal antitrust enforcers, have little else to work with.

III

BEYOND COLLUSION: STRUCTURAL FEATURES OF ALGORITHMIC SYSTEMS

As long as legal analysts of pricing algorithms limit themselves to pattern-matching human conduct and antitrust standards, effective regulation will likely remain limited to scenarios like *Topkins* and *RealPage*: traditionally collusive business arrangements with algorithms relevant only as vectors of information exchange. But an explosion of empirical and theoretical research in the last few years has demonstrated that algorithms are neither mere conduits nor rational agents, and that pricing harms can issue from a much wider variety of algorithmic interactions than contemplated under a conduct-oriented framework.¹¹⁰ Academic fixation on tacit collusion and algorithmic liability does little to aid regulators in the practical problem of detecting and mitigating algorithmic interactions that damage competitive incentives and cause welfare harms, even as pricing algorithms continue to proliferate across consumer markets.

In this Part, I outline three structural features of algorithmic pricing systems, observable in research across a variety of domains, that constrain their behavior and distinguish them from the conduct-centered models commonly discussed in the legal literature: long-term commitment to code, reliance on input data, and production by third parties competing in their own markets. By focusing on the functional dynamics of these systems instead of stretching traditional conduct frameworks to account for their behavior, regulators can design much more effective, targeted interventions to prevent continuing competitive harms.

A. *Commitment and Symmetry*

In a world of human decision-making, pricing strategies are drawn from an essentially infinite space: At any moment, any person in charge of a business can change their mind about what to do next, and could theoretically follow any course of action.¹¹¹ Coordinated action thus requires some mechanism for enforcing a uniform policy, as each member of a classic collusive scheme must be incentivized to

¹¹⁰ See, e.g., *supra* notes 38–41 and accompanying text.

¹¹¹ See Brown & MacKay, *supra* note 63, at 7 (noting that humans are “bound by an incentive compatibility constraint at every opportunity to set prices”).

constantly make and remake the decision to comply.¹¹² Large firm-to-firm variations in market shares, costs, and products tend to make continuing agreement and incentive alignment more difficult, as they affect firms' bargaining power, ability to read coordination signals, price level preferences, and motives to deviate.¹¹³ Thus, traditional cartel theory contemplates a roughly symmetric arrangement in all aspects: firms mirroring each other as much as possible in structure and strategy.¹¹⁴ This idea—that anticompetitive concerted action requires an agreement, which generally requires some level of symmetry—is reflected in antitrust jurisprudence¹¹⁵ as well as scholarship. For example, Ezrachi and Stucke's "predictable agent" scenario assumes that even pricing algorithms developed unilaterally by competing firms will behave roughly symmetrically.¹¹⁶

Pricing algorithms, however, must be committed to code. Every algorithm, whether a simple chain of rules or a complex deep learning model, is defined by a fixed set of data and instructions, and many pricing algorithms—particularly simpler, cheaper ones—are modeled around a limited set of designs.¹¹⁷ Firms using algorithmic pricing tend to update the design of their systems infrequently due to cost, technological, and managerial constraints,¹¹⁸ and thus make long-term commitments to specific and constrained pricing policies in a way that no human can.¹¹⁹ Because of these strong commitments in the algorithmic context, firms can establish fixed, interlocking patterns of interaction without ever

¹¹² See *supra* notes 46–49 and accompanying text (describing incentives for collusive behavior).

¹¹³ See OECD, *Algorithms and Collusion*, *supra* note 10, at 35 (noting that variations in cost, product differentiation, market share, and customer loyalty between oligopolists hinders tacit collusion); see also *supra* Section I.B.

¹¹⁴ See Calvano et al., *Artificial Intelligence*, *supra* note 30, at 3289 (“The conventional wisdom is that asymmetry impedes collusion.”); see also Robert Clark & Jean-François Houde, *Collusion with Asymmetric Retailers: Evidence from a Gasoline Price-Fixing Case*, 5 AM. ECON. J.: MICROECONOMICS 97, 97–98 (2013) (“In most [retail] markets, collusion should be difficult since they feature a large number of asymmetric firms and price-sensitive consumers.”).

¹¹⁵ For example, courts recognize simultaneous conduct—symmetric behavior in time—as a potential sign of collusion, since long lags between individual colluding firms' actions can expose them to customer loss and thus create instability in the agreement. See *In re Text Messaging Antitrust Litig.*, 782 F.3d 867, 877 (7th Cir. 2015) (finding defendants' lack of simultaneous action to weigh against claims of collusion).

¹¹⁶ See EZRACHI & STUCKE, *VIRTUAL COMPETITION*, *supra* note 67, at 61–62 (discussing multiple firms' use of “the algorithm”).

¹¹⁷ See *supra* Section I.A.; see also Musolff, *supra* note 20, at 11–13 (noting that most simple pricing algorithms offered on e-commerce marketplaces like Amazon follow the same essential pattern).

¹¹⁸ See Brown & MacKay, *supra* note 63, at 115, 118.

¹¹⁹ See *id.* at 115 (“[I]n between updates to its algorithm, the firm changes prices based on a fixed set of rules. It is widely thought that humans lack this sort of commitment power.”).

communicating, reaching an agreement, or even observing each other in the market.

Algorithmic commitment enables the market-wide proliferation of discrete, complex, and perfectly replicable pricing strategies without the need for constant human coordination. Economic assumptions about the relationship between market symmetry, strategic symmetry, and concerted action thus break down. Firms may implement symmetric strategies—by opting for similar algorithmic architectures, implementing identical pre-built algorithms sold by third-party vendors, or outsourcing their pricing decisions to the same third-party platform¹²⁰—even when asymmetric market structures and divergent incentives would normally preclude strategic agreement. In these cases, where multiple firms in a market implement the same type of algorithm, a number of economic studies have demonstrated the possibility for collusive algorithmic behavior: monopolistic prices maintained via a reward-punishment scheme.¹²¹ At least one experiment has found that these collusive arrangements tend to disappear when multiple different algorithmic configurations are introduced,¹²² which suggests that traditional harms arising out of collusion are likely to emerge in markets with relatively little diversity among algorithms in use.

However, commitments to asymmetric pricing strategies can also result in durable pricing harms—and, notably, even when the algorithms used are relatively simple and never engage in economic collusion. Researchers have found that mixing simple and complex algorithms in the same market can lead to supracompetitive prices because of non-collusive feedback loops.¹²³ For example, faced with a simple algorithm that always undercuts its competitors—rationally or not—more complex

¹²⁰ Independent development of symmetric strategies is of course possible without algorithms—consider the use of pricing consultants, or the basic rational policy of all sellers in a perfectly competitive market.

¹²¹ Most of these studies use some form of reinforcement learning. See Calvano et al., *Artificial Intelligence*, *supra* note 30, at 3270, 3288 (testing market models with up to four firms and finding that reinforcement learning models could converge on collusive equilibria); Dou, Goldstein & Ji, *supra* note 57, at 4–7 (using reinforcement learning algorithms to model speculator traders in a complex financial market and finding collusive equilibria in some situations); Álvaro Cartea, Patrick Chang, Mateusz Mroczka & Roel Oomen, *AI-Driven Liquidity Provision in OTC Financial Markets*, 22 *QUANTITATIVE FIN.* 2171, 2173 (2022) (finding that collusive arrangements arise when using symmetric algorithms, but not when using asymmetric algorithms).

¹²² See Cartea et al., *supra* note 121, at 2173.

¹²³ See Wang et al., *supra* note 23, at 4, 20–22. Because they do not “learn” from past results, simple rule-based algorithms can easily lead to out-of-control behavior, as in a notable incident where two Amazon booksellers inadvertently entered a price war that brought the price of a textbook past \$23 million. See Olivia Solon, *How a Book About Flies Came To Be Priced \$24 Million on Amazon*, *WIRED* (Apr. 27, 2011, at 15:35 ET), <https://www.wired.com/2011/04/amazon-flies-24-million> [<https://perma.cc/K92R-L86H>].

algorithms may abandon all price cuts as essentially worthless, reducing market-wide pressure to compete on price and ultimately leading to higher prices in the long term.¹²⁴ Another study—one of the few empirical analyses of pricing algorithms—examined pricing patterns among online retailers of over-the-counter drugs and found similar feedback loops driven by asymmetries in update frequency.¹²⁵ Firms that adjust their prices more frequently (say, hourly instead of weekly) can consistently undercut rivals with slower pricing cycles, disincentivizing slower firms from competing on price and eventually inflating market prices overall.¹²⁶ In this case, even a single firm using a faster algorithm or one with a better view of its competitors' prices can "initiate a cycle of consumer harm."¹²⁷ Thus, without ever establishing collusive reward-punishment schemes, firms locked into these asymmetric arrangements by virtue of their strategic commitments can inflict anticompetitive harms by raising prices regardless of consumer demand and suppressing price competition across the market.

Regulators who fail to recognize the effects of strategic commitment on symmetry and asymmetry of behavior will be unequipped to detect and remedy a range of real harms to competitive processes and consumer welfare. Cartel agreements and oligopolistic market structures are no longer necessary for firms to maintain symmetric pricing policies. Meanwhile, standard cartel screening techniques that assume the kind of reward-punishment patterns that arise from traditional collusion—rational cycles of agreement and defection—may fail to recognize new pricing harms driven by the automatic, non-self-regulating algorithmic feedback loops described above.¹²⁸

B. *Scope of Input Data*

Unlike humans, who make decisions based on business data as well as broad, unstructured context from social relationships and general observation, algorithms operate entirely on a precisely defined set of training and input data.¹²⁹ Behavioral analyses of pricing algorithms based on assumptions about human conduct tend to ignore the structured nature of data, treating data exchange as ancillary to

¹²⁴ See Wang et al., *supra* note 23, at 4, 20–22.

¹²⁵ See Brown & MacKay, *supra* note 63, at 110.

¹²⁶ See *id.*

¹²⁷ MacKay & Weinstein, *supra* note 70, at 116–18.

¹²⁸ See Nazzini & Henderson, *supra* note 22, at 15–19 (comparing pricing patterns used to detect traditional cartels with patterns indicating the use of pricing algorithms and concluding that "understanding how 'collusion' works in the world of algorithms is still at its infancy").

¹²⁹ See *supra* Section I.A for a discussion of training and input data.

firm-to-firm communication and agreement. For example, Eyrachi and Stucke describe their “hub and spoke” scenario as competitor firms’ use of a central “brain” or hub, which acts as “the central processor in collecting industry data and setting prices.”¹³⁰ As discussed above, federal courts have generally followed this framing, finding stronger evidence of illegal agreement where an algorithm provider clearly acts as an intermediary and rejecting theories of liability based on allegations of data use in model training alone.¹³¹ And situations without private data exchange, under an antitrust framework, are categorized wholesale into the thorny area of tacit collusion.¹³²

But in algorithmic systems, where input data and encoded pricing strategies are materially separate components¹³³ and where mutually reinforcing patterns are possible without agreement,¹³⁴ input data is more than an auxiliary component of firm communication: It completely controls the scope of what an algorithm “knows” and thus how it behaves. A pricing algorithm trained only on one firm’s internal data and projections has a less complete view of the market than one supplied with that firm’s competitors’ publicly posted prices, which in turn has a less complete view than an algorithm that also incorporates competitors’ private information, such as their internal costs, demand projections, or production goals. When properly accounting for the role of data, the “hub and spoke” breaks down into two distinct scenarios with potentially radically different outcomes: one where competitors’ private information is exchanged or commingled in the data used to train or operate the “hub” algorithm, as in *RealPage*,¹³⁵ and one where the same algorithm is only trained on public data before being distributed to competitors who use it with their own information only.

While instances of private data exchange between competitors are recognizably likely to be anticompetitive, regulators also remain concerned with the potential for harms arising from observations of public information only. Firms using advanced algorithms with deep data-processing capabilities may be able to draw more sophisticated conclusions about the strategies of their competitors—and effectively

¹³⁰ EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 67, at 47–53.

¹³¹ See, e.g., *Gibson v. CENDYN Group, LLC*, No. 2:23-CV-00140-MMD-DJA, 2024 WL 2060260, at *7 (D. Nev. May 8, 2024), *aff’d*, 148 F.4th 1069 (9th Cir. 2025) (“[T]he Court does not find that Plaintiffs have plausibly alleged that Hotel Defendants exchange confidential information with each other—directly or indirectly—by using GuestRev. This matters because exchanging confidential information with your competitors . . . would be more suggestive of an agreement.”); see also *supra* notes 89–96 and accompanying text.

¹³² See *supra* notes 13–15 and accompanying text.

¹³³ See *supra* Section I.A.

¹³⁴ See *supra* Section III.A.

¹³⁵ See *supra* note 28 and accompanying text.

coordinate with them—from public data alone.¹³⁶ Some scholars have even argued that firms seeking coordination with rivals will be able to pattern their price-setting to transparently signal to others their algorithms' core strategic parameters, and that, in fact, rational profit-maximizing firms will always choose maximal transparency in order to invite cooperation.¹³⁷ This argument has drawn criticism, however, for relying on highly specific starting assumptions that do not necessarily reflect the real behavior of firms using algorithmic pricing.¹³⁸

Empirical evidence of openly collusive behavior based on public information remains scarce. To date, only one real-world study—of pricing across German retail gas stations—has observed causal, economically collusive effects from the market-wide use of algorithmic pricing, and, notably, with no evidence of private competitor data exchange.¹³⁹ The authors found that adoption of pricing algorithms led to station-level margin increases of roughly fifteen percent on average, which could be attributed both to improved responsiveness to market conditions (i.e., competitively efficient behavior) and to collusive strategies involving punishment and reward.¹⁴⁰ However, given the unique traits of the German gas market—mandatory real-time price transparency imposed by regulators in 2013¹⁴¹ and a single commodity product—few conclusions can be drawn about the performance of public-data pricing algorithms in more complex information spaces. Without more empirical research, the exact effects of access to private data will remain unclear; these material effects matter little under an antitrust framework. But in an algorithmic world, data is more than a sideshow to agreement, and unraveling the effects of private and public data merits further study.

C. *Third-Party Intermediation*

Finally, while traditional pricing strategies can be mediated by third parties outside the market—for example, industry consultants providing strategic advice to multiple competitors, or major suppliers

¹³⁶ See *supra* notes 56–59 and accompanying text.

¹³⁷ See Bruno Salcedo, Pricing Algorithms and Tacit Collusion 3–4, 15–18 (Nov. 1, 2015) (unpublished manuscript), <https://brunosalcedo.com/docs/collusion.pdf> [<https://perma.cc/P2FE-592T>] (modeling games between firms with “decodable” algorithms and finding that near-monopoly profits always occur); Gal, *supra* note 50, at 84–88.

¹³⁸ See, e.g., O'Connor & Wilson, *supra* note 58, at 3 n.5; Alessio Azzutti, Wolf-Georg Ringe & H. Siegfried Stiehl, *Machine Learning, Market Manipulation, and Collusion on Capital Markets: Why the “Black Box” Matters*, 43 U. PA. J. INT'L L. 79, 109 (2021).

¹³⁹ See Stephanie Assad, Robert Clark, Daniel Ershov & Lei Xu, *Algorithmic Pricing and Competition: Empirical Evidence from the German Retail Gasoline Market*, 132 J. POL. ECON. 723, 726–27 (2024).

¹⁴⁰ See *id.*

¹⁴¹ See *id.* at 730–33.

setting indirect constraints on their buyers' businesses—the easy replicability of software and data allows third parties to distribute pricing algorithms wholesale. The high costs and economies of scale of developing these algorithms, particularly more complex models requiring large amounts of training data, practically ensures that third-party producers and platforms will play a major role in the proliferation of algorithms in a given market. Antitrust scholars tend to envision third parties primarily as platforms for coordinating agreement between competitors, as in Ezechia and Stucke's "hub and spoke" scenario.¹⁴² In fact, these intermediating firms can take many more forms, including pricing platforms like RealPage, independent sellers of user-hosted pricing software, gig economy platforms like Uber that unilaterally set prices, and e-commerce marketplaces like Amazon that host competing sellers (and that may also provide their own pricing tools). They may compete in their own markets against other platforms or algorithm providers, and they may even also compete in the same market as their users, using their own pricing algorithms, and potentially using their privileged access to their users' data.¹⁴³

Third-party intermediators have two key features. First, they directly influence market relationships between competitors, such as by directly controlling the supply of pricing strategies or by controlling firms' access to end consumers. Second, their ability to exert this influence is a trait on which they compete in their own markets.¹⁴⁴ Due to competition in their own markets, third parties face different incentives in algorithm design than firms who design pricing algorithms solely for their own use. Sellers of pricing algorithms, for example, compete against other algorithm sellers and, rationally, should design their algorithms to maximize their own profits—which may involve accounting for the use of their products by multiple users competing against each other in the same market.¹⁴⁵ Thus, on one theory, third-party sellers—assuming a competitive market for algorithms—must avoid designing their algorithms to produce collusive prices between their users that could be easily undercut by a non-user, as that would damage demand for their product.¹⁴⁶

¹⁴² See EZRACHI & STUCKE, *VIRTUAL COMPETITION*, *supra* note 67, at 46–50.

¹⁴³ See, e.g., Liu et al., *supra* note 35, at 7–9 (describing pricing experiments conducted on real products on the Chinese e-commerce platform Tmall by researchers at Tmall's parent company Alibaba).

¹⁴⁴ See Joseph E. Harrington, Jr., *The Effect of Outsourcing Pricing Algorithms on Market Competition*, 68 MGMT. SCI. 6889, 6898–90 (2022).

¹⁴⁵ See *id.*

¹⁴⁶ See *id.* at 6898 (finding that third-party sellers must thus design algorithms to be highly sensitive to unique detections in demand variation).

Similarly, intermediators like Uber that are two-sided platforms experience additional competitive incentives based on the market for their coordinating services. When designing their pricing algorithms, these platforms must account for their impact on network effects as well as the multi-sided nature of competitors' reactions to their pricing changes.¹⁴⁷ And unlike pure pricing platforms like RealPage, two-sided platforms have legitimate business justifications for conduct that might look anticompetitive, such as collecting private data from their users and requiring all sellers to use the same pricing algorithm—though at least one court has suggested that platform businesses like Uber may constitute price-fixing conspiracies regardless.¹⁴⁸ Finally, while some platforms restrict their sellers' ability to set their own prices, platforms like Airbnb and Amazon that provide their own pricing features but allow sellers pricing discretion must account for competition from third-party sellers of pricing algorithms as well.

Algorithmic systems rarely behave like the rational individuals and firms around which antitrust theory is designed. Because they create long-term, highly replicable commitments to discrete pricing strategies, they can entrench anticompetitive market dynamics that can look radically different from traditional collusion. They operate within the constraints of their input data, and they may allow firms to synthesize valuable coordination signals from public data without any kind of private information exchange. And given that digital technologies are often expensive to design and cheap to distribute, pricing algorithms are likely to be produced by third parties or embedded in third-party platforms, with their designs subject to the competitive incentives of those adjacent markets.

IV

TARGETED INTERVENTIONS IN ALGORITHMIC PRICING POLICY

In Part II, I outlined how the prevailing narrative of pricing algorithms as opaque, pseudo-autonomous agents engaging in collusive

¹⁴⁷ See J. Manuel Sanchez-Cartas & Evangelos Katsamakos, *AI Pricing Algorithms Under Platform Competition*, 25 ELEC. COM. RSCH. 4343, 4343, 4348 (Feb. 28, 2024).

¹⁴⁸ See *Meyer v. Kalanick*, 174 F. Supp. 3d 817, 824–25 (S.D.N.Y. 2016) (order denying defendant's motion to dismiss) (asserting that “[t]he fact that drivers may also, in signing up for Uber, seek to benefit from other services . . . is not to the contrary” of the allegation that drivers' agreements would be against self-interest if executed independently). The dispute in *Meyer* ultimately went to arbitration, in which the arbitrator found for Uber. See *Meyer v. Uber Techs., Inc.*, No. 01-18-0002-1956 (Am. Arb. Ass'n Feb. 22, 2020) (Weinstein, Arb.).

conduct has largely failed to support meaningful and innovative regulatory action. A more grounded analysis of these systems—taking into account their structural characteristics, data inputs, and development as market products in their own right—reveals not only that the range of potential harms reaches far beyond tacit collusion, but also that regulatory levers are available beyond antitrust regulation of coordinated conduct. No single legal doctrine is likely to properly address the full range of potential harms; a more varied patchwork of regulatory tools is in order. In this Part, I briefly consider several policy avenues, including data regulations and platform design requirements, and I end by considering how antitrust can still play a role in algorithmic regulation going forward.

A. *Restrictions on Data Use*

Unlike the antitrust laws, data use regulations directly target the inputs to algorithmic systems and, if appropriately targeted, represent a promising avenue for control of algorithmic behavior. U.S. regulators and courts have long held the view that certain types of data sharing between competitors can be inherently anticompetitive,¹⁴⁹ but the post-hoc, case-specific nature of antitrust enforcement in the courts makes litigation a poor fit for data regulation at scale. Legislators and agency policymakers, however, have more latitude to put forth broad principles for limiting private data sharing. Bilateral sharing of sensitive data between competitors is relatively unlikely without some kind of agreement that would likely be a clear antitrust violation, and the value of access to data tends to go up with the volume of data available. Thus, the most probable—and potentially most harmful—data sharing scenarios will likely also involve third-party intermediators, like data brokers or pricing platforms, who deal simultaneously with multiple competing customers.¹⁵⁰ From a regulatory perspective, this is convenient: Third-party intermediators of private data are discrete actors performing a prohibited coordinating function for business purposes, and they

¹⁴⁹ See *In re MultiPlan Health Ins. Provider Litig.*, 789 F. Supp. 3d 614, 641 (N.D. Ill. 2025) (order granting dismissal in part and denying dismissal in part) (citing *In re Broiler Chicken Antitrust Litig.*, No. 1:16-cv-08637, 2025 WL 461407, at *4 (N.D. Ill. Feb. 11, 2025)); *In re RealPage, Inc., Rental Software Antitrust Litig.* (No. II), 709 F. Supp. 3d 478, 511, 518 (M.D. Tenn. 2023) (order denying dismissal of certain plaintiffs' complaints and granting dismissal of other plaintiffs' complaints) (citing the "exchange of commercially sensitive information" as a recognized plus factor supporting an inference of unlawful agreement).

¹⁵⁰ See Competition & Mkts. Auth., *supra* note 69, at 49 (noting that markets involving third-party data intermediaries between competitors may experience particularly high risk of tacit coordination effects).

provide a salient target for monitoring and imposition of penalties.¹⁵¹ Several state proposals for rental pricing reform, including bills passed in Connecticut and under consideration in Massachusetts, follow this logic, banning the use of rental pricing platforms that process private competitor data in their recommendations.¹⁵²

However, more research is required to determine whether and in what cases prohibitions on private data sharing can meaningfully bring down prices in algorithmically priced markets, given potential interdependencies between private and public data. Algorithmic models, particularly more complex machine learning models, commingle vast quantities of data from various sources that may be interdependent.¹⁵³ Proxy heuristics and data interdependence raise the issue of whether private competitor information is in fact a driving factor in raising prices above the competitive level, or if firms can achieve equally harmful outcomes with the use of public data alone. As discussed above, some studies have already found that certain market harms, including supracompetitive prices, can arise even in the absence of private data sharing.¹⁵⁴

Some researchers instead view price transparency as the primary issue, arguing that a prohibition on the use of competitors' prices in algorithms would generally resolve competitive harms resulting from asymmetric algorithms using public data.¹⁵⁵ In this view, a substantial portion of the market harms observed would be remediated even if firms continued to use non-price data to model supply and demand conditions and consumer preferences.¹⁵⁶ A ban on the use of price data would most likely also interfere with those symmetric algorithmic

¹⁵¹ Existing legislative proposals, perhaps recognizing the opportunity for leverage, have focused on third-party providers of algorithmic pricing. *See supra* Section II.C.

¹⁵² *See* 2025 Conn. Acts 25-1 (Nov. Spec. Sess.) (added by H.B. 8002, effective Jan. 1, 2026) (barring the use of revenue management services that use nonpublic competitor data, including if the data is “derived from or otherwise provided by” a competitor); S. 994, 194th Gen. Ct. (Mass. 2025) (same).

¹⁵³ *See supra* notes 26–41 and accompanying text. The challenges of isolating the effects of impermissible data use are best known from the discrimination context. For instance, while the Fair Housing Act bans discrimination based on protected characteristics like race and sex, landlords frequently use tenant screening algorithms that incorporate proxy data for those traits, like income and criminal record. *See generally* Eva Rosen & Philip Garboden, *Algorithms and Racial Discrimination in the US Housing Market*, in *ARTIFICIAL INTELLIGENCE AND THE CITY* 322 (Federico Cugurullo, Federico Caprotti, Matthew Cook, Andrew Karvonen, Pauline McGuirk & Simon Marvin eds., 2024) (discussing the difficulties in applying housing discrimination law to facially race-blind screening algorithms).

¹⁵⁴ *See supra* notes 136–40 and accompanying text.

¹⁵⁵ *See* MacKay & Weinstein, *supra* note 70, at 164–66; EZRACHI & STUCKE, *VIRTUAL COMPETITION*, *supra* note 67, at 229–30 (advocating for reductions in price transparency).

¹⁵⁶ *See* MacKay & Weinstein, *supra* note 70, at 164–66.

arrangements that tend to produce collusive outcomes.¹⁵⁷ However, prohibiting the use of publicly displayed competitor prices would require more intrusive audits by regulatory authorities, who would have to detect actual use of, not just access to, pricing data. Moreover, the distribution of public data is less likely to require the use of third-party data brokers or algorithm platforms;¹⁵⁸ regulators may instead have to monitor the activity of numerous individual competitors in a market.

Prohibitions on the use of public data raise complicated questions of whether legal conceptions of legitimate conduct must be changed in light of new technologies. Traditionally, the law has viewed the act of “intelligently adapting [one’s] business strategy to . . . competitors’ prices or other market conditions” as “a key component of competitive [behavior].”¹⁵⁹ Though the Supreme Court has generally viewed express exchanges of up-to-date price information with suspicion,¹⁶⁰ the general principle that competitors may observe each other’s public behavior has rarely been questioned. As some scholars argue, however, technological advances in price transparency have always caused market disruption and justified regulatory innovation.¹⁶¹ For example, during the 1920s, the popularization of price cards in U.S. grocery stores led to a sea change in retail pricing from ad hoc, individually bargained prices to standardized prices that consumers could compare.¹⁶² This in turn opened the door to retailer innovation in discounting and bundling, leading to a period

¹⁵⁷ See *supra* Section III.A.

¹⁵⁸ California’s 2025 algorithmic pricing prohibitions cover the use of public data but are limited to “common pricing algorithm[s]” used by multiple parties, thus likely permitting firms to continue developing public-data algorithmic systems for their own use. CAL. BUS. & PROF. CODE §§ 16729, 16756.1 (added by Stats. 2025, ch. 338, § 1 (A.B. 325), effective Jan. 1, 2026); see also Mark L. Krotoski & Vinny Sidhu, *California Establishes New Criminal and Civil Liability Targeting Shared Pricing Algorithms and “Coercion,”* PILLSBURY (Oct. 16, 2025), <https://www.pillsburylaw.com/en/news-and-insights/ab-325-shared-pricing-algorithms-liability-california.html> [<https://perma.cc/KC6X-XMEE>] (noting that “[b]espoke, single-firm systems that do not use competitor data” are not covered by the California law).

¹⁵⁹ Peter Georg Picht & Gaspare Tazio Loderer, *Framing Algorithms – Competition Law and (Other) Regulatory Tools* 16 (Max Planck Inst. for Innov. & Competition, Rsch. Paper No. 18-24, 2018); see also *EU Submission on Algorithms and Collusion*, *supra* note 15, at 6.

¹⁶⁰ See Doha Mekki, Principal Deputy Assistant Att’y Gen., U.S. Dep’t of Just. Antitrust Div., Remarks at GCR Live: Law Leaders Global 2023 (Feb. 2, 2023), <https://www.justice.gov/opa/speech/principal-deputy-assistant-attorney-general-doha-mekki-antitrust-division-delivers-0> [<https://perma.cc/JZ6D-W896>] (citing *United States v. U.S. Gypsum Co.*, 438 U.S. 422, 441 n.16 (1978)).

¹⁶¹ See MacKay & Weinstein, *supra* note 70, at 154–55.

¹⁶² See generally Frank Cochoy, Johan Hagberg & Hans Kjellberg, *The Technologies of Price Display: Mundane Retail Price Governance in the Early Twentieth Century*, 47 *ECON. & SOC’Y* 572 (2018) (analyzing the effect of new price display technologies in the early twentieth century on U.S. food prices and finding price formation to be “historically situated socio-technical phenomena”) (cited in MacKay & Weinstein, *supra* note 70).

of “intense price competition” and overall deflation.¹⁶³ Under this historical view, the emergence of new online norms of extreme price transparency and large-scale data analysis might be just as foundational a change warranting a revision of regulatory standards.

B. Design and Transparency Regulations

Another avenue for regulation includes proposals to directly impose regulatory burdens concerning design and transparency on firms that produce and use algorithmic pricing systems. The dominant regulatory discourse around design interventions still tends to track a rational-behavior framework premised on two ideas: first, that algorithms are transparent and auditable in ways that humans are opaque, and second, that an algorithmic system’s behavior is a direct and foreseeable result of its human designers’ intent. Then, as former European Commissioner Margrethe Vestager put it, firms should simply design algorithms that cannot collude: “Like a more honorable version of the computer HAL in the film *2001*, [pricing algorithms] need to respond to an offer of collusion by saying ‘I’m sorry, I’m afraid I can’t do that.’”¹⁶⁴

But science-fiction metaphors offer little clarity as to feasible paths forward. As described in Section I.A, producing even basic human-comprehensible explanations for algorithmic behavior can be a technically difficult, resource-intensive, and uncertain task,¹⁶⁵ and it remains unclear how to actually impose a general non-collusion conduct mandate on an algorithmic system. Regulatory schemes that focus too much on a legal, anthropomorphic idea of algorithmic interaction, with offers, acceptances, and mutual understandings, are likely to turn out both technically infeasible and practically ineffectual. Ironically, a non-collusive algorithmic design requirement might even impose such a heavy cost burden that only a few large, specialized third-party providers of algorithms would survive, creating an oligopoly market in pricing algorithms and attendant harms.¹⁶⁶

Instead of attempting to apply legal frameworks designed around human behavior to automated systems, regulators with a systems view of pricing algorithms might instead focus on limited design regulations addressing specific technical parameters with easily observable results.

¹⁶³ *Id.* at 572.

¹⁶⁴ Vestager Speech, *supra* note 12; see also Beneke & Mackenrodt, *supra* note 52, at 170 (“Authorities could order firms to program their algorithms so as to play competitive instead of cooperative games.”).

¹⁶⁵ See *supra* notes 39–41 and accompanying text.

¹⁶⁶ See *supra* notes 44–45 and accompanying text. For a discussion of how merger control and monopolization enforcement can reduce these risks, see *infra* notes 176–81 and accompanying text.

For example, researchers observing pricing harms from asymmetries in the speed of price updates have proposed limits on update frequency, essentially capping the speed at which one firm might be expected to undercut another.¹⁶⁷ They cite existing successful implementations of similar update frequency limits in the Austrian and Australian retail gas markets and argue that compliance with such a rule would be relatively easy to observe and enforce.¹⁶⁸ In financial markets dominated by algorithmic trading, targeted technical rules designed to maintain overall system integrity are common. For instance, the SEC requires trading venues to implement “circuit breaker” systems that temporarily halt trading in individual securities or market-wide if certain volatility thresholds are exceeded.¹⁶⁹ Though sometimes criticized for imposing costly reporting and disclosure obligations and addressing some market harms less effectively than others, these rules offer a useful example of regulations that impose well-defined duties on specific actors while accounting for the real mechanisms of algorithmic interactions in the system.

Design interventions can also target elements of the larger ecosystems in which pricing algorithms operate, such as third-party marketplace platforms or other intermediators, instead of the algorithms themselves or their input data. Platforms like Amazon provide and shape the baseline environment in which many pricing algorithms are used, and design regulations aimed at shaping market dynamics on these platforms can indirectly counter the anticompetitive effects of algorithmic interactions. One study has shown that modifying the buyer-side user interface of a marketplace platform to prioritize sellers with a history of competitive pricing behavior—thus raising buyer demand for “good” sellers—can produce more competitive prices and increases in consumer surplus across the market overall.¹⁷⁰ Such a modification could be implemented on a real marketplace platform by, say, reordering the list of products displayed to buyers based on sellers’ pricing behavior. Given the massive popularity of marketplaces like Amazon among end consumers, experiments like these suggest that regulators could achieve substantial improvements in consumer welfare by targeting platforms instead of pricing algorithms themselves.

The federal government’s recent settlement proposal in *United States v. RealPage* represents one of the first real-world efforts at direct

¹⁶⁷ See MacKay & Weinstein, *supra* note 70, at 159–64.

¹⁶⁸ *Id.*

¹⁶⁹ Carsten Gerner-Beuerle, *Regulating Automated Trading*, in RESEARCH HANDBOOK ON GLOBAL CAPITAL MARKETS LAW 204, 206–13 (Iris Chiu & Iain MacNeil eds., 2023) (discussing U.S. and EU market integrity regulations).

¹⁷⁰ See Johnson, Rhodes & Wildenbeest, *supra* note 60, at 1843–44.

design regulation of algorithmic pricing systems.¹⁷¹ The proposal limits RealPage’s use of nonpublic competitor information both as training data and as input data: It bars most use of nonpublic price data, geographically localized data, and recent data during training and essentially all use of nonpublic competitor data as inputs to individual recommendations.¹⁷² In addition to algorithm and data limitations, the settlement proposal also imposes restrictions on the design of RealPage’s products, generally requiring RealPage to provide users with more independent control over parameters like the maximum and minimum acceptable price.¹⁷³ Though it remains an open question whether these design requirements will effectively remedy the competitive harms alleged, DOJ’s focus on specific features of RealPage’s systems is a promising indicator of regulators’ ability to embrace a systems approach.

C. Antitrust’s Continuing Relevance

Finally, despite academic pessimism around antitrust founded largely on reductive assumptions about algorithmic behavior, antitrust still has an important role to play in regulating algorithmic pricing harms. As demonstrated in the ongoing *RealPage* and *Yardi* litigations, Section 1 of the Sherman Act remains applicable to cases resembling traditional hub-and-spoke conspiracies, where all three structural factors are favorable: where competitor firms commit to identical pricing strategies, based on private competitor data, and hosted by a single platform provider.¹⁷⁴ In strong cases like these, as discussed above, consent decrees can provide opportunities to shape algorithm design, both directly in their terms and also indirectly by setting forward-looking standards for algorithm providers.¹⁷⁵

Monopolization enforcement under Section 2 of the Sherman Act¹⁷⁶ and merger control can also reduce the concentration of pricing algorithm markets themselves, which in turn reduces the likelihood that entire customer markets adopt synchronized or anticompetitive

¹⁷¹ See U.S. v. RealPage Proposed Final Judgment, *supra* note 6; U.S. v. RealPage Competitive Impact Statement, *supra* note 27 (summarizing terms and impact of proposed settlement).

¹⁷² See U.S. v. RealPage Competitive Impact Statement, *supra* note 27, at 11–17 (describing restrictions on runtime input data use and model training data use).

¹⁷³ *Id.* at 17–20 (imposing restrictions on the design of features like automatic acceptance, target lease number, and “floor” and “ceiling” prices).

¹⁷⁴ See *supra* notes 87–94 and accompanying text.

¹⁷⁵ See *supra* notes 171–73 and accompanying text (discussing *United States v. RealPage* settlement).

¹⁷⁶ Sherman Act of 1890 § 2, 15 U.S.C. § 2 (declaring it unlawful to “monopolize, or attempt to monopolize . . . any part of the trade and commerce among the several States”).

pricing strategies.¹⁷⁷ RealPage’s algorithm, for example, was the product of three competitor acquisitions, and DOJ raised Section 2 claims in its civil enforcement suit, alleging monopolization and attempted monopolization of the market for revenue management products.¹⁷⁸ As noted in the DOJ complaint, exclusionary conduct by a third-party pricing algorithm provider not only affects the pricing algorithm market but can also fuel anticompetitive dynamics in customer markets.¹⁷⁹

Merger control and the regular maintenance of competitive markets may also indirectly lessen the risk of algorithmic pricing harms by reducing the concentration of data in a market, thus increasing the complexity burden on pricing algorithms and reducing synchronization. Current regulatory frameworks for merger control acknowledge the role of data in anticompetitive mergers primarily in terms of foreclosure. For example, a digital platform that acquires a firm producing or brokering data may then exclude competing platforms from using that data.¹⁸⁰ But mergers and combinations of horizontal competitors that involve data consolidation also reduce the informational complexity of the market, potentially making it easier for algorithmic systems to monitor competitors and produce coordinating effects.¹⁸¹ Regulators thus still have the opportunity to reduce algorithmic pricing harms via standard enforcement of market structure.

CONCLUSION

Regulators are right to be concerned about the rapid rise of pricing algorithms across both online and offline markets, as a growing body of scholarship demonstrates that algorithmic interactions can alter traditional competitive behavior, producing elevated prices and other consumer harms. These harms can arise from a wide variety of dynamics, including both traditional patterns of collusion and entirely new interactions structurally unique to algorithmic systems. At the same time, regulators should keep in mind that empirical evidence is scarce,

¹⁷⁷ Academics have also proposed targeting merger review at mergers that make algorithmic coordination more likely. See Michal S. Gal, *Limiting Algorithmic Coordination*, 38 BERKELEY TECH. L.J. 173, 213–20 (2023).

¹⁷⁸ U.S. v. RealPage Amended Complaint, *supra* note 6, at 100–02.

¹⁷⁹ See *id.* at 100 (“RealPage has ensured that rivals cannot compete on the merits unless they enter into similar agreements with landlords, offer to share competitively sensitive information among rival landlords, and engage in actions to increase compliance.”).

¹⁸⁰ See U.S. DEPT. OF JUST. & FED. TRADE COMM’N, MERGER GUIDELINES 25 (2023); Jörg Hoffmann & Germán Johannsen, *EU-Merger Control & Big Data: On Data-Specific Theories of Harm and Remedies* 5–6 (Max Planck Inst. for Innov. & Competition, Rsch. Paper No. 19-05, 2019) (discussing EU regulators’ focus on “absolute foreclosure” from data).

¹⁸¹ See Gal, *supra* note 177, at 216–17 (discussing how a merger involving data acquisition can make algorithmic coordination more efficient).

and that theoretical models are inherently limited in their applicability to real markets. But one thing is clear: Algorithms are not humans or rational agents and do not behave as such. Despite the appeal of extending or adapting antitrust legal theories to algorithms as agents, such an approach critically misunderstands both the mechanisms by which pricing algorithms cause harm and the feasibility of remedies. Instead, regulators must leverage the full range of tools available, targeting specific data uses and system design parameters alongside continued antitrust enforcement in order to ensure that algorithmic pricing technologies are used to benefit consumers and market participants alike.