Media and the AI Black Box

Separating the Enforceable from the Unknown in AI Pricing

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The media's tendency to portray AI as a sentient consumer manipulator allows us to ignore prosecutable actions taken by humans behind the scenes. RealPage, a revenue management service for landlords, exemplifies a company whose AI pricing algorithm appeared to fuel pandemic-era rent surges[1] while remaining beyond regulators' reach. Despite this, the company now finds itself embroiled in a Department of Justice antitrust suit, focusing not on the "nefarious" AI algorithm but on concrete steps that humans took to inhibit competition. Headlines are predictably dour[2] on the topic, however, warning of a coming age where algorithms help companies raise prices ever higher and squeeze the consumer ever tighter.

The scope of concern about pricing algorithms is not overstated: Revenue management software is ubiquitous, and increasingly sophisticated (and difficult to interpret) algorithms will inevitably make their way into these products. Despite this, I argue we are not resigned to our fate. I use RealPage as an example to argue that Section 1 enforcement is still applicable in many cases. I also argue for reviewing an algorithm's source code as a new tool of Section 1 enforcement, while emphasizing that there are parts of the recent literature on algorithmic price collusion that remain outside the bounds of antitrust enforcement. I draw an allusion for these cases to the tacit collusion that has long beguiled academics and enforcers alike. While the specter of algorithmic pricing clouds media narratives, I demonstrate there are steps enforcers can and likely will take to bring the threat to heel.

The revelation of DOJ's suit against RealPage is that it is in many ways an "old school" collusion case. Most of the claims are alleged violations of Sherman Act Section 1, which states that any attempt at coordination or collusion is *per se* illegal. The Justice Department presents quotes from RealPage executives that a "rising tide lifts all boats" (leaving the reader to infer the subtext); they present evidence that RealPage employees pressured landlords not to lower rents from what their pricing algorithm, YieldStar, suggested; and they present evidence that competitively sensitive information was discussed at so-called "user group meetings" that RealPage facilitated for its customers. Taken together, the DOJ would claim this is indirect evidence that YieldStar was recommending supra-competitive prices to landlords and then pressuring them to commit to the high prices. My point, however, is that YieldStar's price recommendation is immaterial to the antitrust case. Coordination is *per se* illegal, regardless of

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[1] "The beauty of RealPage is that it pushes you to go places that you wouldn't have gone if you weren't using it," a consumer testimonial boasted on its website.

[2] "We're Entering an AI Price-Fixing Dystopia." The Atlantic. August 10, 2024. "Beware Algorithms that Could Collude on Prices." The Wall Street Journal. April 1, 2019. "Price Bots can Collude Against Consumers." The Economist. May 6, 2017.

its competitive effects. Thus, we have our first enforceable aspect: Any attempt, contractual or otherwise, by a revenue management service to force compliance with its price recommendation software is *per se* illegal. As a recent ruling[3] allowing a similar case to proceed against Yardi reaffirms, coordination via intermediary is still coordination.

To tackle the thornier question, let's assume there were no overt pressure campaign to stick to recommended prices. The question of whether YieldStar recommends supra-competitive prices becomes germane in determining consumer harm. Before discussing liability and legal remedies, a theoretical interlude on competitive prices and their surprising fragility is necessary.

In the most basic game-theoretic model, two firms competing against each other face a prisoner's dilemma: If we cooperate and set prices higher, we earn higher profits; however, if prices are high, I have a unilateral incentive to undercut you and take all the business for myself. If our products are perfect substitutes, the result is that in equilibrium we are forced to price at marginal cost and earn zero profit. Features can be added to the model to give firms pricing power and allow them to price above marginal cost, namely product differentiation and capacity constraints.

However the economist chooses to model the industry at hand, there will ultimately be a set of prices from which firms cannot unilaterally deviate to increase profit: Call these "competitive" prices. The only equilibrium of this model, absent illegal coordination, is for firms to charge the competitive price.

In contrast to competition, there will also be a set of prices that maximize the profit *of the entire industry*: Call these the "monopoly" or "collusive" prices. Except in extreme cases, both monopoly prices and profits will be higher than competitive prices and profits. (Hence the incentive to collude.) Any price that is higher than the competitive benchmark is deemed supra-competitive, suspect, and a harm to consumer welfare.

When firms interact repeatedly, the prior analysis unravels. The Folk Theorem famously states that any supra-competitive price can arise with repeated interaction, and that firms can "tacitly" learn to collude without ever communicating. The proof of the Folk Theorem is essentially that the threat of a price war deters you from lowering prices, formally called a "trigger strategy" (if we both are charging a high price, we continue to charge a high price; if you ever change your price, I punish you by charging the lowest price possible in perpetuity). Through mechanisms such as price matching and the threat of price wars, firms can arrive over time at a price that is higher than the "competitive" price as defined above. Though concerning, it has largely been accepted that tacit collusion is outside the bounds of antitrust law:

> The courts have been extremely reluctant to convict companies for purely tacit collusion, since that comes close to prohibiting conduct that seems virtually inevitable in an oligopoly setting (for example, responding to a rival's price change in a similar fashion). Moreover, prohibition is not straightforward since it is not altogether clear what action by companies should be proscribed.

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[3] ORDER DENYING DEFENDANTS' JOINT MOTION TO DISMISS in United States District Court for Western District of Washington. Duffy et al. v. Yardi Systems, Inc., et al. No. 2:23-cv-01391-RSL

> For these reasons purely tacit cooperation has been largely outside the reach of the antitrust laws and is likely to remain so unless in particular cases it is clear that some facilitating practice plays a crucial role and unless the courts are persuaded of the practicality of action against it.[4]

Nevertheless, recent research[5] suggests that pricing algorithms may be accelerating tacit collusion at an unprecedented scale. Q-learning agents, used for solving these repeated-interaction, "dynamic" games as described above, have been shown in experimental settings to converge towards apparently collusive outcomes more often than not. To the extent that these experimental results extend to real-world situations, broad integration of Q-learning algorithms into revenue management software poses a potentially grave threat to our ideals of competition. If it becomes clear that this is a particular case, as alluded to above, where dynamic machine learning algorithms are facilitating tacit collusion, then action to limit their use may be warranted. As suggested by Joseph Harrington,[6] Section 5 of the FTC Act, which prohibits unfair methods of competition, could be brought to bear against tacitly collusive pricing algorithms.

The difficulty with any Section 5 enforcement is in determining the scope of the prohibition. Harrington's suggestion is that, if tacit collusion is effectively synonymous with a trigger strategy (which I accept), we can compare outputs of a pricing model to detect evidence of tacit collusion. My claim is that an exceedingly broad class of algorithms would fail this test. For one, price matching algorithms, which are a fundamental approach to retail sales, would likely be construed as tacit collusion. Further, many seemingly innocuous attempts at revenue optimization would likely also fail. A series of economic theory papers[7] suggests, in one case, that *any* pricing algorithm that responds to competitors' prices will result in supra-competitive price; and in another case, that market-level price—e.g., average rent in a metro area—is enough information to eventually facilitate tacit collusion.

Ultimately, "competitive" pricing as defined above may be more tenuous than we would like to think. This represents a genuine unknown about pricing algorithms: Tacit collusion may have been widespread before the advent of algorithmic pricing, but these algorithms may also make it easier and more effective. The concern extends beyond software that makes price recommendations. Software that provides better demand forecasting and the ability to manually experiment with the effects of price changes would likely also facilitate tacit collusion, via "human" rather than "machine" learning. And yet demand forecasting is essential functionality in many industries.

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[4] John E. Kwoka, Jr., and Lawrence J. White. 2009. *The Antitrust Revolution.* New York: Oxford Press

[5] Calvano, Emilio et al. (2020) "Artificial Intelligence, Algorithmic Pricing, and Collusion." American Economic Review; Klein, Timo (2021) "Autonomous Algorithmic Collusion: Q-Learning under Sequential Pricing." RAND Journal of Economics; Abada, Ibrahim and Xavier Lambin (2023) "Artificial Intelligence: Can Seemingly Collusive Outcomes be Avoided?" Management Science.

[6] Harrington, Joseph (2019) "Developing Competition Law for Collusion by Autonomous Artificial Agents." Journal of Competition Law and Economics.

[7] Bresnahan, Timothy (1981) "Duopoly Models with Consistent Conjectures." American Economic Review; Green, Edward and Robert Porter (1984) "Noncooperative Collusion under Imperfect Price Information." Econometrica. Brown, Zach and Alexander MacKay (2023) "Competition in Pricing Algorithms." American Economic Journal: Microeconomics.

In the meantime, I argue that reviewing an algorithm's source code should become an important part of Section 1 enforcement in these collusion cases. Antitrust authorities can subpoena source code that runs and produces a price recommendation, and experts can analyze this code to dissect the nature of the recommendation. I argue a provable attempt to collude is when the algorithm is coded to suggest a collusive price to end-users. This is a different test than suggested above, as the point of AI learning to tacitly collude is that it is *not* explicitly coded. However, source code that explicitly facilitates collusion is arguably more pernicious, and courts would likely accept this kind of code as an attempt at coordination under Sherman Act Section 1. Harrington suggests examining source code for a trigger strategy ("you deviate and I punish," spelled out in the code). I would also suggest that, returning to the definitions of the "competitive" and "collusive" price from above, code whose price recommendation maximizes any kind of *joint* profit objective is an example of explicit coordination. This suggestion comes from the economics literature on detecting collusion[8] where we typically estimate both a competitive and a collusive model and see which fits the data better, but in this case, we can examine the code and know for certain which model is implemented.

While statements like "humans have too much empathy" (from a RealPage employee) are shocking and stoke fears of a dystopian future, I would suggest that coordination still has elements we can pursue. From pressuring others to cooperate, to discussing competitively sensitive information,[9] to writing code for algorithms that suggests collusive prices, there are aspects of this new reality that regulators can isolate and prosecute to mitigate concerns about algorithmic collusion. While a future Section 5 prohibition remains uncertain at best, updated tools and strategies for Section 1 enforcement should invigorate those of us hoping to see competitive balance in AI pricing algorithms.

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[8] Asker, John and Volker Nocke (2021) "Collusion, Mergers, and Related Antitrust Issues." Handbook of Industrial Organization.

[9] See also U.S. v. Agri Stats, Inc. for a case ostensibly about "algorithms" that alleges Section 1 violations for sharing sensitive information.