



## NOTE

## Anticompetitive Interdependence in “Gullible” Pricing Algorithms

Gregory D. Schwartz\*

**Abstract.** Sellers across a wide range of industries increasingly delegate pricing decisions to computers. Their pricing algorithms can improve market efficiency by reacting immediately to changes in supply chains and market demand. But these programs can also aid and conceal harmful anticompetitive behavior. Under the Biden Administration, the Federal Trade Commission expanded the scope of antitrust enforcement and brought claims against such algorithms, even amid concerns that these actions would deter beneficial business conduct.

But to fully address the emerging risks from pricing algorithms, antitrust law would have to be pushed even further. While scholars and agencies scrutinize highly sophisticated artificial intelligence, little attention has been paid to another prevalent threat: simple, “gullible” pricing algorithms. With a few clicks, millions of online retailers can easily implement programs that automatically mimic competing prices. These algorithms—and others like them—can reliably collude on accident, without human agreement or intent. As such, they are common, anticompetitive, and outside the reach of even expanded conceptions of antitrust law.

This Note situates these gullible agents within antitrust literature, examining their prevalence and the challenges they pose to existing enforcement frameworks. As antitrust agencies continue to reassess the breadth of their authority, this Note argues that antitrust law is ill-suited to protect consumer welfare from gullible agents without threatening beneficial business conduct. This Note instead proposes that the users of pricing algorithms be subject to a duty of care regarding the gullibility of their systems.

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## Introduction

In September 2024, Amazon lost its motion to dismiss the “standalone” Section 5 claim filed against it by the Federal Trade Commission (FTC) for unfair competition practices.<sup>1</sup> This ruling was an important victory for the FTC, legitimizing its rare use of Section 5 authority to reach conduct not condemned by other antitrust statutes.<sup>2</sup>

The lawsuit accuses the trillion-dollar<sup>3</sup> conglomerate of—among other things—“manipulat[ing] other online stores’ pricing algorithms into increasing prices.”<sup>4</sup> According to the FTC’s complaint, Amazon carried out a “covert operation” to build an algorithmic tool termed “Project Nessie” to predict the likelihood that online competitors “would follow an Amazon price increase.”<sup>5</sup> When this likelihood was high, Project Nessie would automatically raise prices and maintain those raised prices if Amazon’s competitors followed suit.<sup>6</sup>

The complaint alleges that Amazon had been using and developing Project Nessie for roughly a decade,<sup>7</sup> occasionally pausing the tool to evade detection and ultimately generating over one billion dollars in additional profit.<sup>8</sup> From these facts, the FTC argued that Project Nessie employed an unfair method of competition in violation of 15 U.S.C. § 45, also known as Section 5 of the FTC Act.<sup>9</sup> Notably, the FTC did not plead that Project Nessie violates the Sherman

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1. *FTC v. Amazon.com, Inc.*, No. 23-cv-01495, 2024 WL 4448815, at \*3, \*11-14 (W.D. Wash. Sept. 30, 2024), ECF No. 289 [hereinafter Sealed Order].
  2. See *The FTC and State Case Against Amazon Highlights Risks and Impacts from Using Pricing Algorithms: Not Just Al Gore’s Rhythm*, BCLP (Oct. 23, 2024), <https://perma.cc/2QBM-3MXR> (“The district court’s ruling on Amazon’s third algorithm, Project Nessie, is notable for being the first ‘standalone’ Section 5 claim upheld in federal court in over 40 years.”); see also William E. Kovacic & Marc Winerman, *Competition Policy and the Application of Section 5 of the Federal Trade Commission Act*, 76 ANTITRUST L.J. 929, 941 (2010) (“Aside from [*FTC v. Sperry & Hutchinson Co.*, 405 U.S. 233 (1972)], . . . one needs to go back to the 1960s to find cases in which the Commission succeeded on appeal in a case applying a Section 5 theory.”).
  3. Derek Saul, *Amazon Is a \$2 Trillion Company for the First Time Ever*, FORBES (updated June 26, 2024, 1:02 PM EDT), <https://perma.cc/43MS-8V5Q>.
  4. Complaint [Public Redacted Version] at 119, *Amazon.com*, 2024 WL 4448815 (No. 23-cv-01495), ECF No. 114.
  5. *Id.* at 2, 120.
  6. *Id.* at 120.
  7. See *id.* at 119-20.
  8. *Id.* at 119, 121.
  9. *Id.* at 127. This Note generally discusses the FTC’s authority under Section 5 to regulate unfair methods of competition. The Wheeler-Lea Act amended Section 5 to also include consumer protection authority, discussed briefly in notes 290-93 below and accompanying text.

Act, departing from its approach to Amazon’s other alleged violations.<sup>10</sup> The current view of antitrust enforcement agencies seems to be that such behavior falls outside the Sherman Act’s reach and criminal penalties.<sup>11</sup>

The potential anticompetitive effects of pricing algorithms are not a novel concern. In 2015, Ariel Ezrachi and Maurice Stucke introduced four widely adopted scenarios in which pricing algorithms can facilitate interdependence.<sup>12</sup> First is the *Messenger*, in which algorithms implement human agreements to collude with superior transparency and responsiveness.<sup>13</sup> Next is the *Hub and Spoke*, where a common algorithm across competing firms leads to horizontal alignment.<sup>14</sup> The third scenario is the *Predictable Agent*, where predictable algorithms expand the set of markets susceptible to tacit collusion and enable firms to sustain larger deviations from competitive behavior.<sup>15</sup> Finally, in the *Digital Eye*, the pricing algorithms are sufficiently sophisticated to independently realize the profits from acting as conspirators—removing the need for human agreement, intent, or even knowledge.<sup>16</sup>

All the scenarios pose difficulties for antitrust enforcement. The Messenger and Hub-and-Spoke scenarios allow cartels to maintain more aggressive agreements in more markets, while leaving less evidence of wrongdoing.<sup>17</sup> The Predictable Agent facilitates interdependence without an agreement to coordinate prices, rendering it lawful under the Sherman Act, antitrust’s dominant and criminal enforcement mechanism.<sup>18</sup> It is hard to imagine how the Digital Eye would be prohibited under any existing antitrust

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10. See Complaint [Public Redacted Version], *supra* note 4, at 125-30.

11. See *infra* Part II.A.2; 15 U.S.C. § 1.

12. Ariel Ezrachi & Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition* 7-9 (Univ. of Oxford Ctr. for Competition L. & Pol’y, Working Paper No. CCLP(L)40, 2015), <https://perma.cc/L2DK-VRKM>. For Ezrachi and Stucke’s first publication of their pricing scenarios, see generally ARIEL EZRACHI & MAURICE E. STUCKE, *VIRTUAL COMPETITION: THE PROMISE AND PERILS OF THE ALGORITHM-DRIVEN ECONOMY* 35-81 (2016) [hereinafter EZRACHI & STUCKE, *VIRTUAL COMPETITION*].

13. Ariel Ezrachi & Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition*, 2017 U. ILL. L. REV. 1775, 1784-85.

14. *Id.* at 1787.

15. *Id.* at 1789.

16. *Id.* at 1795.

17. See ANTONIO CAPOBIANCO, PEDRO GONZAGA & ANITA NYESÓ, OECD, *DAF/COMP* (2017) 4, *ALGORITHMS AND COLLUSION—BACKGROUND NOTE BY THE SECRETARIAT* 25-26 (2017), <https://perma.cc/J4N7-NNGN> (describing how facilitating algorithms can allow cartels to avoid price wars); *id.* at 27 (describing how parallel algorithms can allow for coordinated behavior without any explicit communication).

18. Ezrachi & Stucke, *supra* note 13, at 1793-94; U.S. GOV’T ACCOUNTABILITY OFF., GAO-23-105790, *ANTITRUST: DOJ AND FTC JURISDICTIONS OVERLAP, BUT CONFLICTS ARE INFREQUENT* 4 (2023), <https://perma.cc/EN6W-PMPN>.

law,<sup>19</sup> though pricing algorithms do not yet seem capable of making this scenario a reality.<sup>20</sup>

Project Nessie, however, does not fall neatly into any of Ezrachi and Stucke’s scenarios. It does not involve human agreement like the Messenger or Hub and Spoke. Nor does it seem to involve two sophisticated algorithms independently discovering the benefits of interdependence, as occurs in the Digital Eye.<sup>21</sup> Project Nessie may be closest to the Predictable Agent, but, in that scenario, competitors “all recognize that if they each start using a common pricing algorithm, then that can facilitate what is called ‘tacit collusion.’”<sup>22</sup> Here, however, the firms used different algorithms, and only Amazon is alleged to have acted with anticompetitive intent.<sup>23</sup> Taken further, these differences reveal a more troubling possibility: If Amazon’s competitors used sufficiently gullible algorithms—i.e., those that based their prices on Amazon’s price without additional considerations—interdependent pricing would have emerged regardless of Amazon’s design choices. With sufficiently gullible algorithms, Amazon and its competitors could sustain supracompetitive prices without any firm intending to do so.

This scenario poses an ongoing risk to competition. Sufficiently gullible agents are definitionally interdependent on their competitors. The most common and accessible pricing algorithms for online retailers are not Project Nessie-level artificial intelligence (AI) but those that blindly and automatically mimic their competitors’ prices.<sup>24</sup> These simple, “gullible” algorithms are easily tricked into profitability: They do not know when they are colluding to set supracompetitive prices, so they are never tempted to deviate from a cartel. They act like conspirators without intent or agreement,

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19. Ezrachi & Stucke, *supra* note 13, at 1795-96.

20. See Ariel Ezrachi & Maurice E. Stucke, *Algorithmic Tacit Collusion*, in RESEARCH HANDBOOK ON CARTELS 187, 208 (Peter Whelan ed., 2023); Axel Gautier, Ashwin Ittoo & Pieter Van Cleynenbreugel, *AI Algorithms, Price Discrimination and Collusion: A Technological, Economic and Legal Perspective*, 50 EUR. J.L. & ECON. 405, 415 (2020). For discussions of the challenges in reaching cooperation between sophisticated pricing algorithms, see note 274 below.

21. A substantial portion of the pricing decisions on Amazon are likely made by simple rule-based algorithms. See Le Chen, Alan Mislove & Christo Wilson, *An Empirical Analysis of Algorithmic Pricing on Amazon Marketplace*, 2016 PROCS. 25TH INT’L CONF. ON WORLD WIDE WEB 1339, 1339, 1344 tbl.2. The alternative—that Project Nessie worked because competitors also had the sophistication to identify points of profitable cooperations—would represent an unexpected leap in pricing algorithm capabilities. See *infra* note 274.

22. Maurice Stucke, *Pricing Algorithms & Collusion*, 20 TRANSACTIONS: TENN. J. BUS. L. 1113, 1117 (2019).

23. Complaint [Public Redacted Version], *supra* note 4, at 419 (describing the other online stores’ pricing algorithms).

24. See *infra* Part I.A.1.

putting their anticompetitive behavior beyond the current limits of antitrust enforcement. The danger is not merely theoretical—research indicates that simple pricing algorithms can drive supracompetitive prices, particularly when interacting with more advanced systems like Project Nessie.<sup>25</sup> As such, gullible pricing algorithms are an unaddressed risk that undermines the viability of antitrust law’s traditional permissiveness toward mere interdependence between competitors.

Proceeding in four Parts, this Note offers a fifth scenario for Ezrachi and Stucke’s taxonomy—the Gullible Agent. Part I reviews the nature and use of pricing algorithms. Part II explores collusion in traditional antitrust doctrine, the FTC’s recent expansion of its authority, and how both legal theories apply to Ezrachi and Stucke’s four algorithmic scenarios. Part III introduces the novel “Gullible Agent” scenario, demonstrates its present risk, and explains why it eludes existing antitrust law. Finally, Part IV proposes a duty of care under which users must ensure their algorithms are not unreasonably gullible.

## I. Pricing Algorithms

Pricing algorithms are computer programs that automatically set prices.<sup>26</sup> They are not a new phenomenon—British Airways adopted algorithmic pricing in the 1970s<sup>27</sup>—but algorithms have recently become widespread in travel, entertainment, home rentals, insurance, and sharing economy platforms.<sup>28</sup> Dramatic expansions in data collection, computational resources,

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25. See Qiaochu Wang, Yan Huang, Param Vir Singh & Kannan Srinivasan, *Algorithms, Artificial Intelligence and Simple Rule-Based Pricing* 6 (Apr. 14, 2023), <https://perma.cc/T64F-WC8E> (“Current policy efforts have primarily focused on AI vs. AI pricing competition, emphasizing the risks of collusion. However, our findings indicate that AI vs. simple rule-based interactions are even more collusive, potentially leading to prices near monopoly levels.”).

26. OECD, *ALGORITHMS AND COLLUSION: COMPETITION POLICY IN THE DIGITAL AGE* 16 (2017), <https://perma.cc/3VA4-MVKF> (“Pricing algorithms are commonly understood as the computational codes run by sellers to automatically set prices to maximise profit . . .”).

27. Emilio Calvano, Giacomo Calzolari, Vincenzo Denicolò & Sergio Pastorello, *Algorithmic Pricing: What Implications for Competition Policy?*, 55 *REV. INDUS. ORG.* 155, 156 n.1 (2019).

28. See Julian Haessner, Philipp Haessner & Mark McMurtrey, *Dynamic Pricing in Different Industries*, *J. MKTG. DEV. & COMPETITIVENESS*, Dec. 28, 2023, at 83, 85-89 (reviewing dynamic pricing in tickets and reservations for sporting events, movies, concerts, ski resorts, amusement parks, hotels, buses, and planes); Sophie Calder-Wang & Gi Heung Kim, *Algorithmic Pricing in Multifamily Rentals: Efficiency Gains or Price Coordination?* 11 (Aug. 16, 2024) (unpublished manuscript), <https://perma.cc/UFY4-YEEZ> (estimating that roughly 25% of the buildings and 34% of the units in their dataset used algorithmic pricing); Zach Y. Brown & Alexander MacKay, *Competition in Pricing Algorithms*, *AM. ECON. J. MICROECONOMICS*, May 2023, at 109, 149 (“Online sales  
*footnote continued on next page*”)

and online commerce have fueled a “rapid shift” away from human judgment in pricing.<sup>29</sup>

Algorithmic pricing can provide substantial economic and competitive benefits. It can improve market efficiency by reacting immediately to changes in the supply chain and in market demand.<sup>30</sup> By adjusting in real time to factors like stock availability, capacity constraints, and competitors’ prices, algorithmic pricing can help dynamic markets remain closely tied to their shifting equilibria.<sup>31</sup>

But algorithmic pricing can also have the opposite effect, driving market prices above competitive levels. Understanding how these programs function is critical to understanding how they can create such anticompetitive effects. Some of these algorithms are very sophisticated. They can use AI and machine learning to process vast amounts of data,<sup>32</sup> learn from competitors’ behavior, and react with complex strategies.<sup>33</sup> Other algorithms are simple linear functions of competitors’ prices that do not consider any additional inputs.<sup>34</sup> The following Subparts explore how these pricing algorithms work, how they are used, and how they can collude.

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represent an increasing share of many diverse markets, including insurance, accommodations, and automobiles, in addition to retail goods.”); Chris Gibbs, Daniel Guttentag, Ulrike Gretzel, Lan Yao & Jym Morton, *Use of Dynamic Pricing Strategies by Airbnb Hosts*, 30 INT’L J. CONTEMP. HOSP. MGMT., 2, 5-6 (2018) (discussing the adoption of pricing algorithms by Airbnb and Uber).

29. See Salil K. Mehra, *Antitrust and the Robo-Seller: Competition in the Time of Algorithms*, 100 MINN. L. REV. 1323, 1324 (2016).
30. See *id.* at 1337.
31. Christophe Samuel Hutchinson, Gulnara Fliurovna Ruchkina & Sergei Guerasimovich Pavlikov, *Tacit Collusion on Steroids: The Potential Risks for Competition Resulting from the Use of Algorithm Technology by Companies*, SUSTAINABILITY, Jan. 19, 2021, at 1-2, 3 tbl.1.
32. See Emilio Calvano, Giacomo Calzolari, Vincenzo Denicolò & Sergio Pastorello, *Artificial Intelligence, Algorithmic Pricing, and Collusion*, 110 AM. ECON. REV. 3267, 3267, 3270-72 (2020).
33. See, e.g., *Algorithm*, SYMSON, <https://perma.cc/C9FQ-6P7N> (archived Sept. 25, 2025) (accounting for over thirty factors, including inventory, economic situation, weather, margin, customer behavior, platform and salary costs, product quality, market position, and buying trends); Complaint [Public Redacted Version], *supra* note 4, at 120 (“Project Nessie predicted the likelihood that the online store or stores offering the lowest price for a given product would follow an Amazon price increase.”).
34. See, e.g., Olivia Solon, *How a Book About Flies Came to Be Priced \$24 Million on Amazon*, WIRED (Apr. 27, 2011, 3:35 PM), <https://perma.cc/NE6Z-LKM9> (documenting a book retailer on Amazon setting its price at 0.9983 times its competitor’s price and the competitor setting its price at 1.270589 times the retailer’s price). While these retailers changed their algorithms, simple linear pricing remains “typical.” See Brown & MacKay, *supra* note 28, at 111 n.2.

## A. Types of Programs

Pricing algorithms can be categorized as either rule-based or trained.<sup>35</sup> Rule-based algorithms are created with “traditional” programming methods where a software developer explicitly lists rules to govern the algorithm’s behavior.<sup>36</sup> A programmer might, for example, tell an algorithm to lower its price when sales decrease.<sup>37</sup> In contrast, trained algorithms are given data and a goal like maximizing profit, and they use machine learning techniques to independently determine how best to achieve that goal.<sup>38</sup> While trained algorithms are generally more sophisticated, both kinds of algorithms can vary in their complexity, predictability, and response to competition. In practice, certain implementations are much more common than others.

### 1. Rule-based

Rule-based pricing algorithms use a fixed formula to calculate prices.<sup>39</sup> The most common kind of input in these formulas is “competitor-based” data, such as the average or lowest competing price.<sup>40</sup> Other possible inputs include past sales and the time of day or week.<sup>41</sup>

In the online retail space, standard competitor-based pricing algorithms generally include four customizations: which competitor to mimic, where to set the price relative to that competitor, a price floor, and a price ceiling.<sup>42</sup>

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35. For a similar categorization, see “Simple Algorithms” and “Artificial Intelligence” in Ariel Ezrachi & Maurice E. Stucke, *Sustainable and Unchallenged Algorithmic Tacit Collusion*, 17 NW. J. TECH. & INTELL. PROP. 217, 241-55 (2020). The categories here are delimited by programming techniques (i.e., rule-based or trained) as opposed to whether collusive intent is embedded into the program by humans.

36. *What’s the Difference Between AI and Regular Computing?*, ROYAL INST. (Dec. 12, 2023, 2:00 PM), <https://perma.cc/9PCW-RC9N> (“Regular computing, often referred to as traditional or classical computing, . . . relies on a set of predefined instructions being pre-programmed . . .”).

37. See, e.g., *Automate Pricing: Simplify Pricing and Compete for the Featured Offer*, AMAZON, <https://perma.cc/M45E-3U39> (archived Nov. 24, 2025) [hereinafter *Amazon Automation*] (describing Amazon’s sales-based rules).

38. See, e.g., Calvano et al., *supra* note 32, at 3270-71 (describing how a Q-learning pricing algorithm can learn to optimize its price).

39. See Wang et al., *supra* note 25, at 9-10, 10 tbl.1.

40. *Id.* at 9-10; Brown & MacKay, *supra* note 28, at 115.

41. Wang et al., *supra* note 25, at 10.

42. See, e.g., *Repricer: Create a Strategy*, WALMART: MARKETPLACE LEARN, <https://perma.cc/W4V2-PC6P> (archived Nov. 21, 2025); *Create a Pricing Rule*, AMAZON SELLER CENT., <https://perma.cc/JU92-E84R> (archived Nov. 21, 2025) (explaining how to select the compared-against price and the amount to vary from it); *Add SKUs to a Pricing Rule*, AMAZON SELLER CENT., <https://perma.cc/JHZ3-6WSH> (archived Nov. 21, 2025) (explaining how to add price floors and ceilings).

Often, retailers can choose multiple competitors and a dynamic method to determine which one to mimic, such as whichever competitor has the lowest current price.<sup>43</sup> When deciding where to set one’s price relative to the competitor’s, retailers must typically select a fixed percentage or dollar amount.<sup>44</sup> A negative value keeps the user’s price a fixed amount below a competing price, a positive value keeps the user’s price a fixed amount above a competing price, and a value of zero matches the competition’s price exactly.

Many major e-commerce marketplaces have made these algorithms highly convenient for online retailers to implement. Amazon<sup>45</sup> and Walmart<sup>46</sup> offer free, built-in pricing algorithms that their retailers can activate with a few clicks. These offerings typically encourage retailers to follow their competitors’ price changes.

Walmart, for example, allows sellers to set their prices above, below, or equal to the “Buy Box” price or external competitive prices.<sup>47</sup> With the “above” or “below” options, retailers select the specific dollar amount or percentage with which to adjust to their competition.<sup>48</sup> In addition to applying this pricing rule to the Buy Box price, the external price, or the lower of the two, retailers may also choose to match external prices only when those external prices remain lower after the pricing adjustment based on the Buy Box price is applied.<sup>49</sup> Regardless of the option selected, every Walmart item priced using its built-in algorithm will track its competition by a fixed amount or percentage.<sup>50</sup> To be sure, matching or undercutting prices can increase competition, but this depends on whether the competing firms raise their prices in response.

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43. See, e.g., *infra* notes 47-55 and accompanying text.

44. See, e.g., *infra* notes 47-55 and accompanying text.

45. *Amazon Automation*, *supra* note 37.

46. *Walmart Marketplace Repricer*, WALMART MARKETPLACE, <https://perma.cc/SE8G-URTS> (archived Sept. 25, 2025).

47. *Repricer: Create a Strategy*, *supra* note 42. The “Buy Box” is Walmart’s default seller when a customer does not specify between vendors with the same product. Brij Purohit, *How to Win the Walmart Buy Box—Winning Strategies Revealed*, SELLERAPP (Sept. 10, 2024), <https://perma.cc/G8LP-PFUE>. This is a highly lucrative designation, determined based on factors such as the vendors’ respective prices, ratings, quantity in stock, and shipping costs. *Id.*

48. *Repricer: Create a Strategy*, *supra* note 42.

49. *Repricer: Overview*, WALMART: MARKETPLACE LEARN, <https://perma.cc/6S97-32VT> (last updated Sept. 8, 2025) [hereinafter *Walmart Repricer Overview*] (describing Walmart’s “competitive price options”).

50. See *Repricer: Create a Strategy*, *supra* note 42.

Amazon’s repricer options are similarly focused on matching competitors.<sup>51</sup> Until recently, Amazon almost exclusively promoted its repricer’s competitor-based options,<sup>52</sup> and research suggests that retailers have set up their pricing algorithms accordingly.<sup>53</sup> Like Walmart, all competitor-based rules in Amazon’s promotions set prices either as a proportion of, or by a fixed amount from, a competitor’s price, within optional price ceilings and floors.<sup>54</sup> Unlike Walmart, Amazon also offers other rules, such as “Based on sales units,” which set the price based on the seller’s inventory.<sup>55</sup>

Some third-party algorithm vendors offer rule-based functionality, which typically focuses on matching competitors as well. For example, Repricer offers rule-based pricing for Amazon and eBay.<sup>56</sup> Users first set a “Default Pricing Rule” providing the dollar amount or percentage by which to price below or above a competitor.<sup>57</sup> During this step, users can also select a price

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51. Compare Jeniffer Alexander, *Amazon Automated Pricing: Everything You Need to Know*, SELLERAPP (Sept. 4, 2025) <https://perma.cc/5A78-JKLF> (discussing the “Competitive Buy Box,” “Competitive Lowest Price,” and “Competitive External Price” rules), with *Walmart Repricer Overview*, *supra* note 49 (discussing the “Buy Box [S]trategy,” “Competitive [P]rice [S]trategy,” and “External Price [S]trategy” rules).
  52. Until December 2024, Amazon’s “Automate Pricing” page listed “[r]eacting to your competitors’ price changes” as the first reason to automate pricing. *Automate Pricing: Adjust Pricing Quickly and Automatically*, AMAZON, <https://perma.cc/6SZB-BGDx> (archived Nov. 22, 2025). The other reasons were not related to alternative rule options. *Id.* (advertising that automated pricing “only takes a few clicks,” allows users to “focus on other aspects of [their] business,” improves the chances of becoming a Featured Offer via “[s]harp pricing,” and avoids the repricing fees associated with manual changes). The page has since been changed to promote competitor-based and demand-based pricing, *Amazon Automation*, *supra* note 37, although competitor-based rules remain the default option in other Amazon materials, *Create a Pricing Rule*, *supra* note 42, and third-party instructions have yet to follow suit, see, e.g., *Free Amazon Automate Pricing Tool—Review and Pros & Cons*, SELLER ASSISTANT (Mar. 4, 2024), <https://perma.cc/3ZQ8-SBKD> (“Amazon Automate Pricing is a pricing tool that automatically adjusts your product prices against your competition . . .”).
  53. See Chen et al., *supra* note 21, at 1340, 1344 tbl.2 (finding that more than one-third of the top 1,600 bestselling items on Amazon “very likely” use algorithmic pricing that tracks the lowest price of their competitors).
  54. AMAZON SELLER UNIVERSITY, *Intro to Pricing Products in the Amazon Store*, at 06:33-09:37 (YouTube, Sept. 7, 2022) (on file with the Stanford Law Review), <https://perma.cc/TBT4-AQ4N>; *Match Low Price*, AMAZON SELLER CENT., <https://perma.cc/64D8-ZDSQ> (archived Sept. 25, 2025) [hereinafter *Amazon Match Price*].
  55. *Create a Sales-Based Pricing Rule*, AMAZON SELLER CENT., <https://perma.cc/4ZVN-QAKU> (archived Sept. 25, 2025).
  56. REPRICER.COM, <https://perma.cc/39UE-L73E> (archived Nov. 21, 2025). Combined, Amazon, eBay, and Walmart comprise over 90% of U.S. e-commerce by value sold. Complaint [Public Redacted Version], *supra* note 4, at 55 fig. 14.
  57. *Creating an Amazon Repricing Rule*, REPRICER.COM, <https://perma.cc/G9LA-BALK> (archived Nov. 21, 2025); *Creating an eBay Repricing Rule*, REPRICER.COM, <https://perma.cc/F2TS-B6TT> (archived Nov. 21, 2025); REPRICER.COM, *supra* note 56.

floor and ceiling.<sup>58</sup> Next, users can choose between “Advanced Options,” such as selecting specific merchants who should not be considered competitors.<sup>59</sup> The program’s behavior can be adjusted for various scenarios, such as only repricing upward when the user is a Buy Box winner, but the only available default behavior is to track competitors by a fixed amount or percentage.<sup>60</sup> There is no option to consider other market factors, such as consumer sales or inventory changes.

The result of these options is that a remarkably high number of e-commerce prices are automatically set to be near those of competitors.<sup>61</sup> While more sophisticated algorithms are possible, e-commerce platforms and third-party vendors make competitor-based pricing convenient and intuitive. Whether a retailer’s adoption increases competition or hampers it depends on how other retailers respond.

## 2. Trained

Other marketplaces and third-party algorithm vendors allow sellers to set their prices with trained algorithms.<sup>62</sup> While the specifics of these algorithms are often undisclosed, they typically account for a wide variety of factors. They can use historical data to estimate price elasticity; supra-market factors like weather to predict supply and demand changes; and relative product and brand quality to account for the availability of substitutes in the market.<sup>63</sup>

Exactly how these factors are considered is difficult to determine. Trained algorithms are notoriously opaque,<sup>64</sup> and through individualized training, each

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58. See sources cited *supra* note 57.

59. *Creating an Amazon Repricing Rule*, *supra* note 57; *Creating an eBay Repricing Rule*, *supra* note 57.

60. *Creating an Amazon Repricing Rule*, *supra* note 57; *Creating an eBay Repricing Rule*, *supra* note 57.

61. Chen et al., *supra* note 21, at 1340, 1344 tbl.2 (finding that more than one-third of the top 1,600 best-selling items on Amazon use simple rule-based pricing strategies).

62. See, e.g., *Algorithm*, *supra* note 33; Vladimir Kuchkanov, *Dynamic Pricing Algorithms in Retail: The Power of Machine Learning*, COMPETERA (updated June 28, 2025), <https://perma.cc/7TFY-VHZE>; *About Dynamic Promotions*, GOOGLE MERCH. CTR. HELP, <https://perma.cc/G8F3-2FF6> (archived Sept. 25, 2025) [hereinafter *Google Dynamic Promotions*].

63. See, e.g., Marshall Fisher, Santiago Gallino & Jun Li, *A Step-by-Step Guide to Real-Time Pricing*, HARV. BUS. REV., Nov.-Dec. 2023, at 92, 94-101, <https://perma.cc/7EBG-7D6F> (outlining “a step-by-step process for building an AI-powered pricing model that starts by understanding how consumers decide what and where to buy, conducting experiments to measure price elasticity . . . , and then applying optimization tools to set prices that maximize revenue or profit”); *Algorithm*, *supra* note 33.

64. Davide Castelvecchi, *Can We Open the Black Box of AI?*, NATURE NEWS FEATURE (Oct. 5, 2016), <https://perma.cc/A6AW-TWV2>.

algorithm can have a different “mode” of thinking. But it is clear that these algorithms can engage in highly sophisticated behavior. At a minimum, they can decide whether to undercut competitors or price above them.<sup>65</sup> In simulated market environments, trained algorithms have been shown to decode competing algorithms,<sup>66</sup> set supracompetitive prices,<sup>67</sup> and punish deviating rivals.<sup>68</sup> As such, they are often considered categorically more unpredictable, nuanced, and responsive than rule-based systems.<sup>69</sup>

## B. Human Oversight

The dominant form of human involvement with pricing algorithms is to review pricing decisions post hoc to either change the algorithm or shut it off.<sup>70</sup> The alternative—to review prices before implementing them—would require labor and forgo the much-desired speed of algorithmic price adjustments.<sup>71</sup> Even Amazon, which has substantially more capacity than most retailers to check algorithmic recommendations, appears to have given Project

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65. See, e.g., Complaint [Public Redacted Version], *supra* note 4, at 120.

66. Lea Bernhardt & Ralf Dewenter, *Collusion by Code or Algorithmic Collusion? When Pricing Algorithms Take Over*, 16 EUR. COMPETITION J. 312, 322 (2020).

67. Timo Klein, *Autonomous Algorithmic Collusion: Q-Learning Under Sequential Pricing*, 52 RAND J. ECON. 538, 541-42 (2021).

68. See Calvano et al., *supra* note 27, at 161; see also, e.g., Complaint [Public Redacted Version], *supra* note 4, at 118 (“The various elements of Amazon’s anti-discounting conduct—algorithmically punishing sellers for offering lower prices elsewhere, contractually restraining ASB sellers, and systematically disciplining rivals via its first-party anti-discounting algorithm—work together to suppress competition in both relevant markets, thereby preventing even an equally or more efficient rival from attracting a critical mass of either shoppers or sellers.”).

69. See Wang et al., *supra* note 25, at 1-2, 36-37 (distinguishing “simple rule-based models and more sophisticated AI-driven approaches” and discussing “the stochastic and dynamic nature of [reinforcement learning] algorithms”).

70. See, e.g., *Amazon Automation*, *supra* note 37; *Google Dynamic Promotions*, *supra* note 62; *Walmart Repricer Overview*, *supra* note 49.

71. See Robert M. Weiss & Ajay K. Mehrotra, *Online Dynamic Pricing: Efficiency, Equity and the Future of E-Commerce*, VA. J.L. & TECH., Summer 2001, ¶¶ 12-13; EZRACHI & STUCKE, *VIRTUAL COMPETITION*, *supra* note 12, at 61-62 (“When dynamic pricing yields a competitive advantage, no firm can afford the time gap to access whether the algorithm’s suggested price should be implemented.”); *Amazon Automation*, *supra* note 37 (“Why Automate Pricing? . . . Save time and effort[.] Stay focused on your business while prices automatically adjust . . .”). But see *Keep Prices Competitive Wherever You Go*, EBAY: SELLER CTR., <https://perma.cc/S783-BD5G> (archived Nov. 21, 2025) (offering algorithms that recommend prices, rather than set them).

Nessie direct control over pricing.<sup>72</sup> Indeed, the built-in algorithms offered by Amazon and Walmart’s online marketplaces only allow post hoc review.<sup>73</sup>

As a result, market incentives and resource constraints can leave algorithmic price setting in place with little human scrutiny, sometimes with dramatic consequences. In 2011, for example, two book sellers on Amazon Marketplace decided to use pricing algorithms, each based on the other’s book price.<sup>74</sup> Bordeebok set its price at roughly 1.2705 times that of Profnath, while Profnath set its price at roughly 0.9983 times Bordeebok’s.<sup>75</sup> Updating daily, these books likely exceeded ten times their market price in early March, surpassed one hundred times their market price by mid-March, and were priced in the millions by mid-April.<sup>76</sup> The outrageous prices persisted for nearly two months before either vendor noticed.<sup>77</sup> These popular book retailers, with over 250,000 five-star reviews between them,<sup>78</sup> demonstrated how infrequently even established vendors may review their algorithms’ decisions.

While this example is extreme, it reflects the hands-off pricing model that algorithm developers advertise to retailers.<sup>79</sup> Manual pricing requires some fundamental check on the reasonableness and motivation of pricing changes, but sellers with automatic pricing can easily miss when their algorithms make mistakes and become uncompetitive. Though this lapse carries anticompetitive risks,<sup>80</sup> antitrust scholars and enforcement agencies have focused instead on how algorithms can enable collusion through more sophisticated anticompetitive strategies.<sup>81</sup>

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72. See Complaint [Public Redacted Version], *supra* note 4, at 417 (discussing Amazon’s practice of occasionally “paus[ing]” its algorithm, suggesting that the algorithm would otherwise automatically change prices).

73. See, e.g., *Amazon Automation*, *supra* note 37; *Walmart Repricer Overview*, *supra* note 49.

74. Michael Eisen, *Amazon’s \$23,698,655.93 Book About Flies*, IT IS NOT JUNK (Apr. 22, 2011), <https://perma.cc/HP56-SSHX>.

75. *Id.*

76. See *id.* (detailing the books’ prices in April 2011). Extrapolating from available data for April, both books likely first exceeded \$1,000 on March 8 and \$10,000 on March 18. See *id.* Bordeebok manually reset its price soon after Profnath dropped its price to \$106.23 on April 19. *Id.*

77. *Id.*

78. *Profnath: About Seller*, AMAZON, <https://perma.cc/J5DS-389K> (archived Sept. 25, 2025); *Bordeebok: About Seller*, AMAZON, <https://perma.cc/6JWU-3BJ4> (archived Sept. 25, 2025).

79. See *Amazon Automation*, *supra* note 37.

80. See *infra* Part III.

81. See, e.g., Ezrachi & Stucke, *supra* note 13, at 1794 (“One should acknowledge, however, that evolution dictates that the stronger, more powerful algorithms will likely prevail  
*footnote continued on next page*”)

## II. Regulating Interdependence

The detection, prosecution, and punishment of concerted horizontal price and output restraints is the cornerstone of modern antitrust enforcement in the United States.<sup>82</sup> The economic benefits of this effort have been enormous,<sup>83</sup> though they are built upon a sometimes murky distinction between two forms of interdependence.

In the archetypal case of prohibited interdependence—collusion—firms in a concentrated market agree to set profit-maximizing prices rather than compete in earnest.<sup>84</sup> This agreement may require certain assurances for the cartel to be stable.<sup>85</sup> When firms agree to set supracompetitive prices, each agent has an incentive to break the agreement. Supracompetitive prices are, by definition, those that firms could profitably lower to capture more consumers.<sup>86</sup> As such, cartels often require not just that firms agree on a strategy, but also that they can stabilize that strategy by monitoring others’ adherence and punishing defectors.<sup>87</sup>

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and dominate. . . . A decision not to opt for the most advanced algorithm may be irrational.”). See generally Complaint [Public Redacted Version], *supra* note 4.

82. William E. Kovacic, Robert C. Marshall, Leslie M. Marx & Halbert L. White, *Plus Factors and Agreement in Antitrust Law*, 110 MICH. L. REV. 393, 398 (2011).
83. ROBERT H. BORK, *THE ANTITRUST PARADOX: A POLICY AT WAR WITH ITSELF* 263 (1978) (praising the per se ban against horizontal price fixing and market divisions and concluding that “[i]ts contributions to consumer welfare over the decades have been enormous”).
84. Brendan Ballou, *The “No Collusion” Rule*, 32 STAN. L. & POL’Y REV. 213, 214 (2021) (“In a classic price-fixing conspiracy, firms directly agree to raise or maintain prices for competing products and establish mechanisms by which to detect and punish defectors.”); Jonathan Masur & Eric A. Posner, *Horizontal Collusion and Parallel Wage Setting in Labor Markets*, 90 U. CHI. L. REV. 545, 549 (2023). The term “interdependence” is not universally understood as a superset of collusion. See William H. Page, *Tacit Agreement Under Sherman Act Section 1*, 81 ANTITRUST L.J. 593, 599 (2017) (defining interdependence as a form of collusion that “oligopolists cannot rationally avoid and that courts cannot profitably penalize or enjoin”). But its meaning within this Note is not atypical. See Christopher R. Leslie, *Antitrust’s Interdependence Paradox*, 111 VA. L. REV. 787, 792 (2025) (“[I]nterdependent decision-making does not constitute collusion so long as each decisionmaker acts independently, without discussion or coordination.”).
85. Richard A. Posner, *Oligopoly and the Antitrust Laws: A Suggested Approach*, 21 STAN. L. REV. 1562, 1574 (1969) (“[I]t seems improbable that prices could long be maintained above cost in a market, even a highly oligopolistic one, without some explicit acts of communication and implementation.”).
86. Ai Deng, *What Do We Know About Algorithmic Tacit Collusion?*, ANTITRUST, Fall 2018, at 88, 89 (“[B]oth [competitors] are better off if they cooperate (say, raise prices or reduce output). But at the same time, if I know that my competitors are raising prices, I have an incentive to lower my prices to steal the business and increase my revenue.”).
87. Christopher R. Leslie, *Antitrust Amnesty, Game Theory, and Cartel Stability*, 31 J. CORP. L. 453, 464 (2006).

The need for successful cartels to police and monitor their members has traditionally limited the risk of collusion in many markets.<sup>88</sup> Stable interdependence is more feasible where a variety of “plus factors” exist, including product homogeneity, market concentration, price transparency, the speed of competitive responses, and the number of alternatives available to consumers.<sup>89</sup> In markets with fewer of these factors, collusion can become more costly to effect, harder to conceal, and less rewarding to the participants.<sup>90</sup>

But firms can also act like conspirators absent a collusive agreement. This second form of interdependence is tacit collusion—also called conscious parallelism or mere interdependence.<sup>91</sup> Tacit collusion is the per se legal practice where firms jointly set supracompetitive prices not by explicit agreement, but through the rational calculus of competitors’ probable behaviors.<sup>92</sup> Many of the plus factors recognized in antitrust analysis facilitate tacit collusion as well. For example, after the Chilean government required gas stations to report their prices on a public government website, margins increased by an average of 9%.<sup>93</sup>

The legality of tacit collusion is controversial, and recent changes within the FTC have sought to condemn more of its forms.<sup>94</sup> As pricing algorithms

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88. See Margrethe Vestager, Comm’r, Eur. Comm’n, Remarks at the Bundeskartellamt 18th Conference on Competition: Algorithms and Competition (Mar. 16, 2017), <https://perma.cc/AQ6Y-3VRM>.

89. See U.S. DEP’T OF JUST. & FTC, MERGER GUIDELINES § 2.3.B (2023), <https://perma.cc/K2AJ-3CWC>; AUTORITÉ DE LA CONCURRENCE & BUNDESKARTELLAMT, ALGORITHMS AND COMPETITION 18 (2019), <https://perma.cc/6XHE-GZFW>.

90. See Leslie, *supra* note 84, at 794-96 (describing how concentrated markets make collusion easier by reducing negotiating costs, easing concealment, and increasing each firm’s relative profit); LOUIS KAPLOW, COMPETITION POLICY AND PRICE FIXING 289 (2013) (“When the number of firms is larger, coordinating on a common price . . . tends to be more difficult . . .”). This is not to suggest that the presence of enough factors eliminates the need for overt actions entirely.

91. Page, *supra* note 84, at 595 nn.10-12.

92. *Brooke Grp. Ltd. v. Brown & Williamson Tobacco Corp.*, 509 U.S. 209, 227 (1993); see also Louis Kaplow, *On the Meaning of Horizontal Agreements in Competition Law*, 99 CALIF. L. REV. 683, 718 (2011) (describing how the illegality of price fixing “flows from acts that clothe it using certain types of communication”).

93. Fernando Luco, *Who Benefits from Information Disclosure? The Case of Retail Gasoline*, AM. ECON. J.: MICROECONOMICS, May 2019, at 277, 277-78, 293-94. For potential mechanisms behind this phenomenon, see David P. Byrne & Nicolas de Roos, *Learning to Coordinate: A Study in Retail Gasoline*, 109 AM. ECON. REV. 591 (2019), which finds that “price leaders use price experiments to test rivals’ willingness to coordinate, to signal their intentions, and to create a mutual understanding of a coordinated pricing strategy among rivals,” *id.* at 592.

94. See FTC, NO. P221202, POLICY STATEMENT REGARDING THE SCOPE OF UNFAIR METHODS OF COMPETITION UNDER SECTION 5 OF THE FEDERAL TRADE COMMISSION ACT 13-16  
*footnote continued on next page*

become increasingly capable facilitators of interdependence, antitrust’s reach over algorithmic pricing will turn on the ongoing debate over tacit collusion.

### A. Shifting Theories

Despite several notable critiques, courts have interpreted Section 1 of the Sherman Act to require evidence of an agreement.<sup>95</sup> While the “unfair methods of competition” authority under Section 5 of the FTC Act offers broad enforcement power, standalone Section 5 claims were rare for the decades leading up to the Biden Administration.<sup>96</sup> In 2022, the FTC set out a broader conception of Section 5 that distinguished its analysis from that of the Sherman Act’s rule of reason.<sup>97</sup> The FTC’s expanded interpretation has found some success in court,<sup>98</sup> although its ultimate future remains tenuous.<sup>99</sup>

#### 1. Traditional prohibitions

Section 1 of the Sherman Act prohibits anticompetitive agreements, barring collusion *per se*.<sup>100</sup> However, as discussed above, stable, supracompetitive interdependent pricing can exist absent an agreement.<sup>101</sup> An extensive debate over the legality of tacit collusion began with Donald

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(2022) [hereinafter SECTION 5 POLICY STATEMENT], <https://perma.cc/9NQJ-594G>; *infra* Part II.A.2. The future of this project is uncertain, underscoring its controversial nature. Compare Tim Cornell, Luke Dembosky, Avi Gesser & Ted Hassi, *The Federal Trade Commission Bureau of Consumer Protection Under the Second Trump Administration: Top 10 Things to Know About Priorities, Enforcement, and Case Law Developments*, DEBEVOISE & PLIMPTON: INSIGHTS & PUBLICATIONS (Apr. 29, 2025), <https://perma.cc/N3V3-E4Z3> (“The dissents written by Chair Ferguson and Commissioner Holyoak during Chair Khan’s term signal that the change in leadership at the FTC under the second Trump administration will likely bring a number of policy changes. We anticipate, for example, that the FTC will be less aggressive in seeking civil penalties under Section 5 . . . .”), with Leon B. Greenfield, Hartmut Schneider, Jennifer Milici, Dominic Vote, Perry A. Lange & Jonathan R. Wright, *Meet the New Boss, Not So Different from the Old Boss? Antitrust in the Trump Era*, WILMERHALE (June 2, 2025), <https://perma.cc/LVQ3-9G2J> (“One of the most telling early indications about federal antitrust enforcement in the Trump Administration is what the new leaders at the FTC and DOJ have *not* done. . . . The current Commission has yet to rescind the 2022 Section 5 statement.”).

95. See *infra* Part II.A.1.

96. Lina M. Khan, *Section 5 in Action: Reinvigorating the FTC Act and the Rule of Law*, 11 J. ANTITRUST ENF’T 149, 149-52 (2023); Kovacic & Winerman, *supra* note 2, at 941-42.

97. See *infra* Part II.A.2.

98. See, e.g., Sealed Order, *supra* note 1, at 22-24.

99. See *infra* notes 152-59 and accompanying text.

100. 15 U.S.C. § 1. Section 2 of the Sherman Act addresses monopolization, which is outside the scope of this Note.

101. See *supra* Part II.

Turner’s 1962 article, in which he argued that condemning such behavior would be inappropriate.<sup>102</sup> When firms set prices or output, they are inevitably aware of their competitors’ behavior.<sup>103</sup> To penalize firms for considering that information would create an unacceptably blurry line between lawful and unlawful conduct, making enforcement unworkable for antitrust agencies and unfair to businesses.<sup>104</sup>

Richard Posner responded that interdependent pricing produces the same anticompetitive effects, regardless of whether firms have formed an agreement.<sup>105</sup> Although his arguments “loomed large” for decades,<sup>106</sup> the narrower reading of the Sherman Act is now black-letter law.<sup>107</sup> Posner has since revised his personal position,<sup>108</sup> and while Louis Kaplow and others continue to advocate a broader interpretation,<sup>109</sup> courts have definitively held

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102. See Donald F. Turner, *The Definition of Agreement Under the Sherman Act: Conscious Parallelism and Refusals to Deal*, 75 HARV. L. REV. 655, 666 (1962). For a more thorough description of this debate, see Mehra, note 29 above, at 1340-43.

103. See Turner, *supra* note 102, at 666 (“[E]ach seller in [a supracompetitive oligopoly], in refraining from price competition, is not agreeing with his competitors but simply throwing their probable decisions into his price calculus as impersonal market facts. . . . [I]t seems questionable to call the behavior of oligopolists in setting their prices unlawful when the behavior in essence is identical to that of sellers in a competitive industry. Particularly is this so when the behavior involved, setting the ‘profit-maximizing’ price in light of all market facts, is not only legally acceptable but vitally necessary to make competitive markets function as they are supposed to function.”).

104. *Id.* at 669-70; Maureen K. Ohlhausen, Acting Chairman, U.S. FTC, *Should We Fear the Things that Go Beep in the Night? Some Initial Thoughts on the Intersection of Antitrust Law and Algorithmic Pricing 4* (May 23, 2017), <https://perma.cc/U55L-8MN2> (“In a free market, individual actors are free to set their prices on the basis of all the information legally available to them.”).

105. Posner, *supra* note 85, at 1575-78.

106. Keith N. Hylton, *Oligopoly Pricing and Richard Posner*, ANTITRUST SOURCE, Oct. 2018, at 1, 1.

107. See *infra* notes 110-11 and accompanying text.

108. See *In re Text Messaging Antitrust Litig.*, 782 F.3d 867, 874 (7th Cir. 2015) (Posner, J.) (“Louis Kaplow . . . argues that tacit collusion should be deemed a violation of the Sherman Act. That of course is not the law, and probably shouldn’t be.”); Hylton, *supra* note 106, at 10 (“[Q]uestions of application and detail bedevil any serious effort to take the more aggressive approach to Section 1 enforcement urged by Posner in his 1969 article. Posner’s *Text Messaging 2015*, while not entirely rejecting the thesis of his 1969 article, is a sobering exploration of the problems of application.”); see also Richard A. Posner, *Review of Kaplow, Competition Policy and Price Fixing*, 79 ANTITRUST L.J. 761, 763 (2014) (book review) (acknowledging that he “didn’t sufficiently appreciate the force of Turner’s doubts about the feasibility of an antitrust remedy for tacit collusion”).

109. See, e.g., Kaplow, *supra* note 92, at 795 (arguing that “agreement” does not “contain any distinction among modes of interdependence, ranging from plain interdependence to old-fashioned cartel arrangements”).

that conscious parallelism alone does not constitute an “agreement.”<sup>110</sup> Consequently, the Sherman Act has a well-known gap that permits price coordination so long as it occurs without communication or facilitating practices, regardless of whether it results in supracompetitive pricing.<sup>111</sup>

Some scholarship has suggested that Section 5 of the FTC Act should be used to fill that gap,<sup>112</sup> though the view is far from ubiquitous.<sup>113</sup> Legislative history provides that the FTC Act is a “broad and flexible statute,”<sup>114</sup> intended to create discretionary antitrust enforcement authority over “unfair competition.”<sup>115</sup> The Supreme Court held early on that any conduct violating the spirit of the antitrust laws is a Section 5 violation,<sup>116</sup> though it never addressed the extent to which standalone Section 5 claims may reach conduct not covered by the Sherman Act or Clayton Act. The FTC pursued standalone

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110. See *In re Chocolate Confectionary Antitrust Litig.*, 801 F.3d 383, 397-98 (3d Cir. 2015) (describing interdependent pricing as a “‘fact of life’ in oligopolies” and noting that “courts have no effective remedy for the problem” (quoting *In re Baby Food Antitrust Litig.*, 166 F.3d 112, 122 (3d Cir. 1999))); *Rsrv. Supply Corp. v. Owens-Corning Fiberglas Corp.*, 971 F.2d 37, 50 (7th Cir. 1992) (“[I]t is close to impossible to devise a judicially enforceable remedy for ‘interdependent’ pricing. How does one order a firm to set its prices *without regard* to the likely reactions of its competitors?”); Masur & Posner, *supra* note 84, at 548-49 (“Explicit collusion has long been illegal under antitrust law . . . . On the other hand, tacit coordination in price setting—that is, parallel pricing—is legal, though there has been extensive debate over the practice.”).
111. Mehra, *supra* note 29, at 1328.
112. See, e.g., OECD, *supra* note 26, at 38 (“Section 5 could be used to tackle algorithmic collusion if the agency could show that, when developing the algorithms, defendants were either motivated to achieve an anticompetitive outcome or were aware of their actions’ natural and probable anticompetitive consequences.”); Aneesa Mazumdar, Note, *Algorithmic Collusion: Reviving Section 5 of the FTC Act*, 122 COLUM. L. REV. 449, 453 (2022).
113. E.g., Thomas Dahdouh, *Section 5, the FTC and Its Critics: Just Who Are the Radicals Here?*, COMPETITION J., Sept. 1, 2011, at 1, 1-2 (collecting sharp criticisms of independent Section 5 enforcement); Gregory J. Werden, *Unfair Methods of Competition Under Section 5 of the Federal Trade Commission Act: What Is the Intelligible Principle?* 39 (May 10, 2023) (unpublished manuscript), <https://perma.cc/58Q6-URLE> (arguing that the bounds of Section 5’s unfair methods of competition prohibition “can be found in the Sherman and Clayton Acts even if the [Section 5] prohibition reaches a bit further”).
114. Neil W. Averitt, *The Meaning of “Unfair Methods of Competition” in Section 5 of the Federal Trade Commission Act*, 21 B.C. L. REV. 227, 229, 232-35 (1980).
115. See S. REP. NO. 63-597, at 13 (1914) (“[I]t would be better to put in a general provision condemning unfair competition than to attempt to define the numerous unfair practices . . .”).
116. *FTC v. Sperry & Hutchinson Co.*, 405 U.S. 233, 239 (1972); see *FTC v. Ind. Fed’n of Dentists*, 476 U.S. 447, 454 (1986).

Section 5 claims for decades, until a series of circuit court decisions in the 1980s demanded a more concrete definition of unfair practices.<sup>117</sup>

In *Boise Cascade Corp. v. FTC*, for example, the Ninth Circuit held that the FTC must demonstrate evidence of an agreement or an actual effect on competition to succeed on a Section 5 claim.<sup>118</sup> Whereas in *E.I. Du Pont de Nemours & Co. v. FTC (Ethyl)*, the Second Circuit determined that Section 5 only extends beyond other antitrust laws to reach per se pernicious conduct or anticompetitive intent.<sup>119</sup> The court clarified that it is the corruption of market forces—not undesirable market outcomes—that defines an antitrust violation.<sup>120</sup> The courts as a whole have bound the FTC to this rule,<sup>121</sup> rejecting arguments that “the FTC could, whenever it believed that an industry was not achieving its maximum competitive potential, ban certain practices in the hope that its action would increase competition.”<sup>122</sup>

Following these decisions, the FTC pulled back from bringing standalone Section 5 claims. After years of calls for guidance,<sup>123</sup> the Commission published its 2015 statement,<sup>124</sup> which “made Section 5 essentially coterminous with the Sherman Act” as it tethered unfair methods of competition to the Sherman Act’s rule of reason standard.<sup>125</sup> While the 2015 statement was not “traditional” in the sense that it codified a settled interpretation of Section 5,<sup>126</sup> the statement has been seen as the culmination of the FTC’s enforcement trend since the 1980s<sup>127</sup> and was in effect during a period of continued minimal

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117. See, e.g., *Off. Airline Guides, Inc. v. FTC*, 630 F.2d 920, 927 (2d Cir. 1980); *Boise Cascade Corp. v. FTC*, 637 F.2d 573, 576-77 (9th Cir. 1980); *E.I. Du Pont de Nemours & Co. v. FTC (Ethyl)*, 729 F.2d 128, 138-39 (2d Cir. 1984).

118. 637 F.2d at 577.

119. 729 F.2d at 138.

120. *Id.* at 138-39.

121. For further analysis, see Maureen K. Ohlhausen, *The Elusive Role of Competition in the Standard-Setting Antitrust Debate*, STAN. TECH. L. REV., Winter 2017, at 93, 117.

122. *Ethyl*, 729 F.2d at 138-39.

123. See Joshua D. Wright, Comm’r, FTC, Section 5 Recast: Defining the Federal Trade Commission’s Unfair Methods of Competition Authority, Remarks at the Executive Committee Meeting of the New York State Bar Association’s Antitrust Section 4-5, 5 n.11 (June 19, 2013), <https://perma.cc/G7MJ-3LEY>.

124. Statement of Enforcement Principles Regarding “Unfair Methods of Competition” Under Section 5 of the FTC Act, 80 Fed. Reg. 57056 (Sept. 21, 2015).

125. Khan, *supra* note 96, at 151.

126. Wright, *supra* note 123, at 3-4 (listing a wide variety of proposed interpretations); Statement of Enforcement Principles Regarding “Unfair Methods of Competition” Under Section 5 of the FTC Act, 80 Fed. Reg. at 57057 (dissenting statement of Commissioner Maureen K. Ohlhausen, describing the 2015 statement as “an unbounded interpretation” of Section 5).

127. See Khan, *supra* note 96, at 151; see also Mark W. Bayer, Annamarie A. Daley & Kendall Millard, *Federal Trade Commission Provides Statement of Enforcement Principles Regarding* footnote continued on next page

standalone Section 5 enforcement.<sup>128</sup> Under the 2015 guidance, Section 5 claims usually would not be brought absent an agreement, and certainly not absent anticompetitive intent.<sup>129</sup>

## 2. Extending the FTC Act

The 2015 statement was short-lived, however, as the FTC voted to rescind the policy statement in 2021<sup>130</sup> and issued a new statement in 2022 that took a broader view of the FTC’s authority.<sup>131</sup> This policy argued that “unfair methods of competition” do not necessarily involve anticompetitive harm or anticompetitive intent.<sup>132</sup> Rather, unfair methods of competition are those that go beyond competition on the merits by involving per se pernicious uses of market power, those that tend to have anticompetitive effects, or both.<sup>133</sup> These principles are applied on a sliding scale: If the evidence is weak for one consideration, it must be strong for the other.<sup>134</sup>

This shift could trigger many of Turner’s concerns.<sup>135</sup> The 2022 statement is clear in its view that Section 5 has the authority to condemn practices that facilitate tacit coordination,<sup>136</sup> but it is unclear how feasible or reasonable it will be to prosecute firms for making rational business decisions based on legally acquired information.<sup>137</sup> Indeed, then-Commissioner Christine

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*Unfair Methods of Competition*, LEXOLOGY (Aug. 18, 2015), <https://perma.cc/3B8Y-RQXY> (advising that the 2015 statement “does not appear to be a radical change from traditional antitrust enforcement”).

128. MAJORITY STAFF OF SUBCOMM. ON ANTITRUST, COM. & ADMIN. L. OF H. COMM. ON THE JUDICIARY, 116TH CONG., INVESTIGATION OF COMPETITION IN DIGITAL MARKETS: MAJORITY STAFF REPORT & RECOMMENDATIONS 402 (2020) (reporting that the FTC brought only one standalone Section 5 claim under the 2015 guidelines).

129. Ezrachi & Stucke, *supra* note 13, at 1795 (“The application of § 5 of the FTC Act, for example, was contingent on anticompetitive motive or intent. . . . [W]e completely remove the legal concept of intent. In doing so, we exclude § 5 from the available enforcement tool-box.”).

130. *FTC Rescinds 2015 Policy that Limited Its Enforcement Ability Under the FTC Act*, FTC (July 1, 2021), <https://perma.cc/4YQJ-Q3E4>.

131. See SECTION 5 POLICY STATEMENT, *supra* note 94, at 1, 6-10, 13.

132. *Id.* at 4; see also Dahdouh, *supra* note 113, at 15 (arguing that Section 5 “does not require evidence of actual intent to harm competition”).

133. See SECTION 5 POLICY STATEMENT, *supra* note 94, at 9.

134. *Id.*

135. See *supra* note 102 and accompanying text.

136. See SECTION 5 POLICY STATEMENT, *supra* note 94, at 13.

137. See *supra* note 108. Reasoning that some kinds of information tend to facilitate tacit collusion while offering minimal procompetitive benefits, scholars have proposed reducing the tacit collusion problem by making certain information exchanges illegal. Peter C. Carstensen & Annkathrin Marschall, *Pooling and Exchanging Competitively*  
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Wilson’s dissent to the policy statement echoed Turner’s concerns, arguing that “[d]ue process demands that the lines between lawful and unlawful conduct be drawn clearly.”<sup>138</sup> Applying the FTC Act may be more sensible than the Sherman Act since the FTC does not levy criminal penalties,<sup>139</sup> but the fundamental difficulty of distinguishing tacit collusion from ordinary conduct still applies.

Practically, however, this expanded conception appears to rarely condemn interdependence where there is not at least anticompetitive intent. While not clarified as such in the 2022 Statement, per se pernicious uses of market power (such as coercive, collusive, or deceptive methods) appear unlikely to occur without anticompetitive intent, even if the intent itself cannot be proven. If the practice is not per se pernicious, it would need a very strong tendency to reduce competition for the extended FTC Act to apply.<sup>140</sup> Such a tendency also signals anticompetitive intent. To implement and sustain a practice from which deviation offers short-term profits requires either ignorance of the potential profit or knowing sacrifice of the immediate gain to reduce competition. Where anticompetitive tendency is particularly high, ignorance is unlikely.

This understanding of Section 5’s relationship to intent mirrors the statement’s incorporation of *Ethyl*, where the court required a showing of either agreement, per se pernicious behavior, or “some indicia of oppressiveness,” such as intent or the absence of a legitimate reason for the challenged conduct.<sup>141</sup> All four elements are at least suggestive of anticompetitive intent, even if the intent itself is not proven. This understanding likewise mirrors the statement’s incorporation of *Boise*, which required either anticompetitive intent or indicia that allowed the court to

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*Sensitive Information Among Rivals: Absolutely Illegal Not Just Unreasonable*, 92 U. CIN. L. REV. 335, 383-84 (2023); Joseph E. Harrington, Jr. & Christopher R. Leslie, *Horizontal Price Exchanges*, 44 CARDOZO L. REV. 2301, 2348-50 (2023). Tacit collusion, however, does not always require such overt sharing.

138. FTC, Dissenting Statement of Commissioner Christine S. Wilson Regarding the “Policy Statement Regarding the Scope of Unfair Methods of Competition Under Section 5 of the Federal Trade Commission Act” 1 (Nov. 10, 2022), <https://perma.cc/B8CK-X5SA>.

139. 15 U.S.C. § 56(b).

140. See SECTION 5 POLICY STATEMENT, *supra* note 94, at 9 (describing the sliding scale).

141. 729 F.2d 128, 140 (2d Cir. 1984) (“[I]n the absence of proof of a violation of the antitrust laws or evidence of collusive, coercive, predatory, or exclusionary conduct, business practices are not ‘unfair’ in violation of § 5 unless those practices either have an anticompetitive purpose or cannot be supported by an independent legitimate reason.”).

“assume that there was a ‘deliberate restraint on competition.’”<sup>142</sup> Indeed, the statement argues that the FTC need not show anticompetitive intent, not that Section 5 covers methods of competition where anticompetitive intent does not exist.<sup>143</sup> Part of this conclusion is derived from evidence of legislative concern over the difficulty in proving anticompetitive intent, although the analysis also draws on Posner-esque statements from one senator that anticompetitive effects concern the public regardless of firm intent.<sup>144</sup>

Consequently, though the statement opens the possibility of standalone Section 5 claims based on a variety of considerations, intent appears to remain crucial in the FTC’s expanded view. Without intent, most other indicia of oppressiveness will not be present, requiring a strong showing of anticompetitive tendency<sup>145</sup> and evoking skepticism from the courts.<sup>146</sup> It is little surprise, then, that the FTC has relied heavily on indicators of Amazon’s intent in the Project Nessie case<sup>147</sup> and early treatment by scholars has continued to center intent.<sup>148</sup>

Effectively requiring anticompetitive intent through a direct showing or indicia would help assuage Turner’s concerns<sup>149</sup>: Anticompetitive intent and its artifacts are hardly a part of innocent, ordinary business conduct. The result is that if pricing algorithms engage in tacit collusion and there is no evidence that humans intended that collusion, Section 5 would still rarely, if ever, apply.

As such, the 2022 policy statement appears to dramatically expand Section 5 authority while maintaining the fairness and administrability that motivated Turner’s position. That is not to say the policy statement resolves

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142. See SECTION 5 POLICY STATEMENT, *supra* note 94, at 7 n.43 (quoting *Boise Cascade Corp. v. FTC*, 637 F.2d 573, 581 (9th Cir. 1980)).

143. *Id.* at 4-5.

144. *Id.* at 5 & n.22.

145. *Id.* at 9 (describing the sliding scale).

146. See *supra* notes 141-42 and accompanying text.

147. Complaint [Public Redacted Version], *supra* note 4, at 127 (“Amazon designed and used its Project Nessie pricing system for the sole purpose of manipulating other online stores into increasing their prices.”); Plaintiffs’ Opposition to Amazon’s Motion to Dismiss at 19, *FTC v. Amazon.com*, No. 23-cv-01495, 2024 WL 4448815 (W.D. Wash. Feb. 6, 2024), 2024 WL 4101976, ECF No. 149 (relying on anticompetitive intent to support its standalone unfair methods of competition claims).

148. Compare, e.g., Ariel Ezrachi & Maurice E. Stucke, *The Role of Secondary Algorithmic Tacit Collusion in Achieving Market Alignment*, 26 VAND. J. ENT. TECH. L. 461, 494-95 (2024) (arguing that the FTC’s Section 5 claim against Project Nessie can succeed if anticompetitive intent is found, whereas claims against unaware hub-and-spoke participants cannot), with Ezrachi & Stucke, *supra* note 13, at 1795 (noting in 2017 that “[t]he application of § 5 of the FTC Act” to the Predictable Agent Scenario is “contingent on anticompetitive motive or intent” and that “remov[ing] the legal concept of intent. . . . exclude[s] § 5 from the available enforcement tool-box”).

149. See *supra* notes 103-04 and accompanying text.

antitrust’s interdependence problem. Section 5’s lack of criminal sanctions yields a weaker deterrent compared to the Sherman Act,<sup>150</sup> despite the potential for tacit collusion to create the same harmful effects as those of traditional cartels.<sup>151</sup> The statement’s flexible framework also creates uncertainty for businesses. But it at least provides that some antitrust remedy will usually be available where there are anticompetitive intent and effects.

The longevity of the FTC’s 2022 policy statement remains unclear. The expansion of Section 5 has been largely attributed to then-Chair Lina Khan.<sup>152</sup> While Khan has expressed hope that the FTC will continue to pursue an aggressive enforcement agenda,<sup>153</sup> now-Chair Andrew Ferguson is poised to embrace a more traditional interpretation of the FTC’s legal authority.<sup>154</sup> Though commentators disagree over whether the 2022 statement will be officially withdrawn,<sup>155</sup> Chair Ferguson frequently dissented from Khan’s

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150. See Ezrachi & Stucke, *supra* note 35, at 256 (arguing that the weak antitrust liability outside of the Sherman Act leaves tacit collusion “ripe for further exploration by companies”).
151. See Kaplow, *supra* note 92, at 812-13 (“[T]he economic substance [between mere interdependence and classic cartels] is indistinguishable.”). Indeed, the inefficiencies from mere interdependence may be greater than those from coordinated pricing. See *id.* at 812 (“[S]uccessful interdependent oligopoly pricing can be worse than old-fashioned explicit cartels because the latter might be able to rationalize production . . . .”); see also *id.* at 813 (“[I]f prohibited communications are almost always necessary for successful coordinated oligopoly pricing[,] . . . the only distinguishing feature of an agreement requirement beyond mere interdependence is that it would exonerate coordinated oligopoly pricing in those few cases in which the danger of successful—more likely, more prolonged—coordination is greatest.”).
152. Cf. Andrew Ross Sorkin, Ravi Mattu, Bernhard Warner, Sarah Kessler, Michael J. de la Merced, Lauren Hirsch & Ephrat Livni, *What to Watch as Lina Khan Finally Takes on Amazon*, N.Y. TIMES (Sept. 27, 2023), <https://perma.cc/6NG7-MWUT> (presenting the FTC’s suit against Amazon, including the claims regarding Project Nessie, as Lina Khan’s career “com[ing] full circle”).
153. See Lina M. Khan, Samuel A.A. Levine & Stephanie T. Nguyen, *After Notice and Choice: Reinvigorating “Unfairness” to Rein in Data Abuses*, 77 STAN. L. REV. 1375, 1428-29 (2025).
154. See Christopher N. Olsen, Maneesha Mithal & Taylor Stenberg Erb, *Shaping Consumer Protection: What to Expect from Incoming Chairman Ferguson’s FTC*, WILSON SONSINI (Dec. 19, 2024), <https://perma.cc/2ZAX-JS3H>; Kevin B. Goldstein, Conor Reidy, Jean Vardaramatos & Ryan Chen, *Trump’s Antitrust Strategy Continues to Take Shape with New FTC Picks*, WINSTON & STRAWN (Dec. 17, 2024), <https://perma.cc/W7NE-PVCA> (predicting a more cautious approach to expanding the FTC’s authority).
155. Contrast Boris Bershteyn, Karen M. Lent, Tara L. Reinhart & David P. Wales, *Keep Your Seatbelts Fastened: The Antitrust Ride May Not Be Over*, SKADDEN (Jan. 14, 2025), <https://perma.cc/W43H-4NUK> (“The FTC likely will withdraw the 2022 policy statement on Section 5 and revert to the more limited historical approach.”), with Greenfield et al., *supra* note 94 (“One of the most telling early indications about federal antitrust enforcement in the Trump Administration is what the new leaders at the FTC and DOJ have *not* done. . . . The current Commission has yet to rescind the 2022 Section 5 statement.”).

enforcement actions when he was a commissioner, arguing for that more traditional view.<sup>156</sup> Commentators have noted Ferguson’s strong positioning of himself as against large technology companies, but these statements have thus far centered on content moderation, not anticompetitive conduct.<sup>157</sup> Even if the 2022 statement remains officially in force, the Commission’s practice could focus on its more established authority.

To be sure, the FTC’s shift to a narrower Section 5 is not certain. Early commentators have also flagged the “increasingly bipartisan view that antitrust enforcement should be more aggressive.”<sup>158</sup> But regardless of whether the FTC’s future interpretation of Section 5 reflects its 2015 statement, 2022 statement, or something in between, there are looming anticompetitive threats from pricing algorithms that even the 2022 expanded view cannot address. And insofar as the expanded interpretation already blurs the line between prohibited conduct and ordinary business, such threats may require solutions from outside of existing antitrust law.<sup>159</sup>

## B. Applied to Algorithms

Ezrachi and Stucke have developed four widely adopted scenarios—the Messenger, the Hub and Spoke, the Predictable Agent, and the Digital Eye—in which algorithms can create and facilitate collusion or tacit collusion in markets where such behavior was previously infeasible.<sup>160</sup> While they still

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156. See, e.g., FTC, Dissenting Statement of Commissioner Andrew N. Ferguson *In the Matter of Guardian Service Industries, Inc.* 1-2 (Dec. 4, 2024), <https://perma.cc/NZB6-G24Z> (“[A]s I have warned before, we must always act within the boundaries Congress has imposed on our authority.”).

157. See, e.g., Cecilia Kang & David McCabe, *Trump Picks Andrew Ferguson to Lead Federal Trade Commission*, N.Y. TIMES (Dec. 10, 2024), <https://perma.cc/4D9B-6CNY>.

158. Goldstein et al., *supra* note 154.

159. See *infra* Part IV.

160. EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 12, at 36-37. On the use of Ezrachi and Stucke’s terminology by scholars and leaders in antitrust enforcement, see, for example, Michal S. Gal, *Limiting Algorithmic Coordination*, 38 BERKELEY TECH. L.J. 173, 181 (2023); and Terrell McSweeney & Brian O’Dea, *The Implications of Algorithmic Pricing for Coordinated Effects Analysis and Price Discrimination Markets in Antitrust Enforcement*, ANTITRUST MAG., Fall 2017, at 75, 75-76. Internationally, commentators often use functionally identical categories. See Steven Van Uytsel, *Artificial Intelligence and Collusion: A Literature Overview*, in ROBOTICS, AI AND THE FUTURE OF LAW 155, 157 (Marcelo Corrales, Mark Fenwick & Nikolaus Forgó eds., 2018) (“The Secretariat of the Organization for Economic Co-operation and Development (OECD) follows [Ezrachi and Stucke’s] categorization but uses different names. The OECD distinguished between monitoring algorithms, parallel algorithms, signaling algorithms, and self-learning algorithms. Niccolò Colombo terms these four categories as follows: classical digital cartel, inadvertent hub-and-spoke, tacit algorithmic collusion and dystopian virtual reality.” (footnotes omitted)); see also Steven Van Uytsel, *The Algorithmic Collusion Debate: A Focus on (Autonomous)*  
*footnote continued on next page*

create challenging enforcement problems, these established algorithmic collusion scenarios are all either governed by traditional antitrust law (Messenger, Hub and Spoke), captured by the FTC’s expanded approach to Section 5 (Predictable Agent), or not regarded as an imminent possibility (Digital Eye).

The Messenger and Hub-and-Spoke scenarios involve agreements.<sup>161</sup> As such, both are traditional antitrust violations, albeit through different means. While they may create evidentiary challenges by facilitating less overt agreements,<sup>162</sup> any legal questions can be straightforwardly addressed with existing antitrust doctrine. In the Predictable Agent scenario, firms intend to effect tacit collusion but make no explicit or tacit agreement. Thus, the scenario is addressable under the FTC’s expanded view.<sup>163</sup> The Digital Eye, however, involves no human agreement, intent, or even knowledge.<sup>164</sup> While this brings the scenario beyond even the successful application of expanded Section 5 authority, such algorithmic behavior does not yet appear feasible with current systems; real-world markets are complex, and it is challenging to learn a winning strategy involving short-term losses.<sup>165</sup> Antitrust enforcement agencies are thus in an uneasy but tenable space, with at least an answer to each of the feasible collusive scenarios.

*Messenger.*—In the first scenario, humans agree to collude and use pricing algorithms to execute the collusion.<sup>166</sup> For example, in *United States v. Topkins*, competitors discussed their desired pricing strategy and only used algorithms to implement their agreement.<sup>167</sup>

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*Tacit Collusion*, in ALGORITHMS, COLLUSION AND COMPETITION LAW 1, 4 & n.13 (Steven Van Uytsel, Salil K. Mehra & Yoshiteru Uemura eds., 2023) (reviewing the widespread adoption of Ezrachi and Stucke’s four scenarios in official documents and scholarly literature).

161. Ezrachi & Stucke, *supra* note 13, at 1784 tbl.1.

162. See *A Conversation with FTC Commissioner Andrew Ferguson Hosted by Alden Abbott*, MERCATUS CTR.: ANTITRUST & COMPETITION (June 13, 2024), <https://perma.cc/DB5F-UUUK> (reporting Chair Ferguson’s comments on how algorithms enable collusion, such as making “the collusion, at least the intentionality of the collusion . . . not . . . super obvious”). *But see* Defendant Information Relative to a Criminal Action—In U.S. District Court at 3, *United States v. Topkins*, No. 15-cr-00201 (N.D. Cal. Apr. 6, 2015), ECF No. 1 (describing how co-conspirators discussed their desired prices before creating an algorithm to carry out any changes).

163. Ezrachi & Stucke, *supra* note 13, at 1784 tbl.1.

164. *Id.*

165. Ezrachi & Stucke, *supra* note 20 (“[M]uch is still uncertain as to the capacity of future reinforced-learning or deep-learning algorithms to reach conscious parallelism with no human intervention. Doubts as to learning algorithms’ ability to sustain collusion refer to their increased sophistication[,] which would make alignment difficult.”).

166. EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 12, at 39-45.

167. Plea Agreement at 3-4, No. 15-cr-00201 (N.D. Cal. Apr. 30, 2015).

Algorithms can increase transparency, responsiveness, and predictability—changing cartel tolerance to market conditions such that collusion becomes feasible where it was not possible before.<sup>168</sup> With increased transparency, cartels can better identify when a member is deviating from their inflated prices.<sup>169</sup> With increased responsiveness, cartels can respond to the deviation by near-instantly lowering their prices—thereby removing the incentive to deviate.<sup>170</sup> With increased predictability, cartels can suffer from fewer misunderstandings, allowing them to collude with fewer explicit, incriminating communications.<sup>171</sup>

The use of pricing algorithms here can create significant evidentiary challenges for antitrust enforcers. These algorithms require enforcers to monitor markets that were previously resistant to collusion and look beyond traditional indicators of collusive conduct.<sup>172</sup> Yet where human agreement to collude is present, the behavior is decidedly unlawful under Section 1 of the Sherman Act.<sup>173</sup>

*Hub and Spoke.*—In the second scenario, a single pricing algorithm is used to set prices for multiple users.<sup>174</sup> Suppose, for example, that competitors in a market see the efficiencies offered by algorithmic pricing but lack the resources to develop such software for themselves. These competitors outsource the task: They find an upstream supplier “hub,” and each competitor “spoke” sets all their prices with the same algorithm.<sup>175</sup> In the online retail space, such algorithms are often offered by the platform itself.<sup>176</sup>

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168. Vestager, *supra* note 88 (“Every cartel faces the risk that its members will start cheating each other as well as the public. If everyone else’s price is high, you can gain a lot of customers by quietly undercutting them. So whether cartels survive depends on how quickly others spot those lower prices, and cut their own price in retaliation. By doing that quickly, cartelists can make sure that others will be less likely to try cutting prices in the future. And the trouble is, automated systems help to do exactly that.”).

169. EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 12, at 39.

170. Mehra, *supra* note 29, at 1348-49; U.S. DEP’T OF JUST. & FTC, HORIZONTAL MERGER GUIDELINES § 7.2 (2010), <https://perma.cc/LG5B-WWEF> (discussing how “swift competitive reaction times diminish each firm’s prospective competitive reward from attracting customers away from its rivals”).

171. *See* Mehra, *supra* note 29, at 1349-50.

172. *Id.* at 1354, 1356-57 (describing how pricing algorithms may leave a weaker paper trail as cartels can generate credibility through “mutual expectation [of] swift retaliation,” as opposed to “face-to-face secret meetings”).

173. *See* Mazumdar, *supra* note 112, at 470.

174. *See* EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 12, at 46-55.

175. *See, e.g., The Best AI Repricer for Amazon & Walmart*, FLASHPRICER, <https://perma.cc/9UGM-QSLK> (archived Sept. 25, 2025).

176. *See supra* notes 45-46 and accompanying text.

This behavior is not necessarily illegal, particularly if the software vendor is not also a competitor in the downstream market.<sup>177</sup> However, the centralization of pricing algorithms provides the opportunity for the vertical supplier to facilitate a traditional hub-and-spoke conspiracy.<sup>178</sup> Consequently, without ever communicating directly with each other, these competitors can “find” their prices aligned.

That these arrangements are not necessarily illegal can make it challenging for antitrust enforcers to show collusion. Firms may choose to use an upstream supplier to effectuate an anticompetitive agreement, or they may do so because they merely lack the resources to create pricing algorithms in-house. Pricing algorithms also improve with scale<sup>179</sup>—more data and more computational power mean that an upstream algorithm market is likely to coalesce as the buyers have independent business reasons to use the largest product.

As such, in recent hub-and-spoke cases, European Union courts held that only participants who were aware of the collusion engaged in illegal conduct.<sup>180</sup> U.S. antitrust law would likewise look to whether, in using the algorithms, firms intend a clearly illegal result and know that the illegal result is probable.<sup>181</sup> This can make proving agreement more challenging, although the Sherman Act remains applicable and the fundamental goal of antitrust enforcement remains the same.<sup>182</sup>

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177. See EZRACHI & STUCKE, *VIRTUAL COMPETITION*, *supra* note 12, at 47, 52.

178. For a brief explanation of hub-and-spoke conspiracies, see *Howard Hess Dental Laboratories Inc. v. Dentsply International, Inc.*, 602 F.3d 237, 255 (3d Cir. 2010).

179. *How Does AI Pricing Work?*, SYMSON, <https://perma.cc/E9FQ-2Q43> (archived Sept. 25, 2025).

180. Case C-74/14, *Eturas v. Competition Council of the Republic of Lithuania*, ECLI:EU:C:2016:42, ¶ 45 (Jan. 21, 2016) (holding that “if it cannot be established that a travel agency was aware of that message, its participation in a concertation cannot be inferred from the mere existence of a technical restriction implemented in the system at issue . . . unless it is established on the basis of other objective and consistent indicia that it tacitly assented to an anticompetitive action”).

181. *United States v. U.S. Gypsum Co.*, 438 U.S. 422, 444 (1978) (concluding “that action undertaken with knowledge of its probable consequences and having the requisite anticompetitive effects can be a sufficient predicate for a finding of criminal liability under the antitrust laws”).

182. Richard A. Powers, Deputy Assistant Att’y Gen., U.S. Dep’t of Just., Remarks at 2020 International Competition Network Annual Conference: Cartel Working Group Plenary: Big Data and Cartelization (Sept. 17, 2020), <https://perma.cc/8ULM-42BN> (“[I]f an intermediary, such as a programmer or platform, facilitates a conspiracy among competitors to use a common pricing algorithm for the purpose of fixing prices, under U.S. law, we could prosecute both the competitors and the intermediary who facilitated the illegal agreement.”).

Like messenger algorithms, this scenario is a current concern—several private suits already contend that competitors and their software providers participate in a hub-and-spoke conspiracy.<sup>183</sup>

Note that since similar algorithms are more likely to cooperate,<sup>184</sup> upstream suppliers increase the risk that algorithms independently decide to collude with each other without an agreement between firms. Such an event would be classified as one of the two following scenarios: Predictable Agent or Digital Eye, despite the involvement of a hub. Which of these two scenarios applies depends on whether the independent collusion was predictable and intended by the firms.

*Predictable Agent.*—In the third scenario, competitors independently realize that if they each implement similar predictable algorithms, those algorithms will independently begin to collude without express or tacit communication between firms.<sup>185</sup> If two firms implement competitor-based pricing, for example, they can predict that supracompetitive interdependent pricing will occur.<sup>186</sup> In this way, firms can intentionally implement competitor-based pricing with the aim of tacit collusion.<sup>187</sup> These firms do not need to explicitly communicate or form an agreement. The interdependent pricing comes from the algorithms themselves, albeit with the knowledge and intent of their users.

As there is no agreement between the parties, the Sherman Act would be inapplicable.<sup>188</sup> Charges under the expanded view of Section 5 of the FTC Act would likely depend on whether the FTC can show anticompetitive intent or artifacts of anticompetitive intent.<sup>189</sup> Ezechachi and Stucke argue that intent is discoverable in this scenario because of the predictability of the algorithms.<sup>190</sup> That is, anticompetitive intent exists where firms unilaterally create such algorithms knowing that the result will be collusive pricing. However, this

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183. See, e.g., Class Action Complaint at 1-4, *Gibson v. MGM Resorts Int'l*, No. 23-cv-00140 (D. Nev. Jan. 25, 2023); Daniel Mandrescu, *When Algorithmic Pricing Meets Concerted Practices—The Case of Partneo*, LEXXION (June 7, 2018), <https://perma.cc/SME4-WNBP>.

184. EZRACHI & STUCKE, *VIRTUAL COMPETITION*, *supra* note 12, at 79.

185. Stucke, *supra* note 22, at 1116.

186. Indeed, if the algorithms consist of purely competitor-based pricing and net-greater-than-one modifiers, supracompetitive pricing is guaranteed. See, e.g., Solon, *supra* note 34 (describing the two runaway Amazon booksellers, where pricing of  $n_0 \times 0.9983$  and  $n_1 \times 1.270589$  resulted in both booksellers increasing their price by a factor of  $0.9983 \times 1.270589 = 1.2684289$ , or 26.84% every day).

187. EZRACHI & STUCKE, *VIRTUAL COMPETITION*, *supra* note 12, at 56 (“[E]ach firm unilaterally creates an algorithm but knows that the industry-wide use of pricing algorithms will facilitate tacit collusion.”).

188. See 15 U.S.C. § 1.

189. See *supra* notes 140-46 and accompanying text.

190. EZRACHI & STUCKE, *VIRTUAL COMPETITION*, *supra* note 12, at 66-69.

intent may be difficult to ascertain, as there are legitimate business reasons to use pricing algorithms.<sup>191</sup> Since it is in the nature of pricing algorithms to make markets more transparent and predictable, it can be difficult for enforcers to distinguish between the innocent use of algorithms and intentions to collude.<sup>192</sup>

*Digital Eye.*—In this final scenario, highly sophisticated AI algorithms learn on their own to collude with each other.<sup>193</sup> Like the Predictable Agents, there is no express or tacit agreement between humans; but unlike the Predictable Agents, there is also no human intent.<sup>194</sup> The AI pricing algorithms are unpredictable: Their decisions are made in a “black box” that defies human inquiry.<sup>195</sup> The collusion truly originates in the algorithm, and humans might not even know that supracompetitive prices exist.<sup>196</sup> Without agreement or anticompetitive intent, antitrust enforcement has little response.<sup>197</sup>

This is not to say the development of such AI is completely anticompetitive. The increased market transparency would cause prices to go down and up faster in accordance with actual demand and scarcity, offering better allocative efficiency.<sup>198</sup> There can also be procompetitive responses as AI improves the abilities of pricing algorithms to realize unseen opportunities and profitably lower prices.<sup>199</sup> However, it remains concerning that antitrust enforcers lack adequate tools to handle algorithms’ vast anticompetitive potential.

While such pricing systems do not appear to be currently feasible in practice,<sup>200</sup> they have been demonstrated in simplified, simulated environments. Algorithms are already capable of cooperating in controlled,

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191. See *supra* notes 30-31 and accompanying text. *But see* SECTION 5 POLICY STATEMENT, *supra* note 94, at 10-12 (suggesting that parties that offer justifications for prima facie unfair methods of competition will face a challenging burden).

192. EZRACHI & STUCKE, *supra* note 13, at 1794.

193. EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 12, at 71.

194. *Id.* at 77-78 (“In our last scenario, humans are further detached from the algorithms’ tactical and strategic decisions. They don’t know whether, when, or for how long the algorithms have been tacitly colluding. There is no evidence of anticompetitive intent. We can no longer assume that humans intended to create the conditions for tacit collusion.”).

195. See Castelveccchi, *supra* note 64.

196. EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 12, at 77-78.

197. *Id.* at 79; EZRACHI & STUCKE, *supra* note 13, at 1784.

198. See *supra* notes 30-31 and accompanying text.

199. See *supra* notes 30-31 and accompanying text.

200. Gautier et al., *supra* note 20 (“[W]hile some scientific studies have shown that algorithms can collude or facilitate collusion under specific constraints, there have been no real-life reported cases of algorithmic tacit collusion . . .”).

limited-resource environments<sup>201</sup> and optimizing market interactions to put upward pressure on prices.<sup>202</sup> Some scholars suggest that tacit collusion via machines is inevitable.<sup>203</sup>

The imminence of unpredictable AI pricing systems depends heavily on the markets in which they operate. While the Digital Eye scenario involves unpredictable AI pricing systems learning to coordinate pricing behavior, it would be significantly easier for AI to find collusive solutions if its competitors used more gullible or pro-social algorithms.<sup>204</sup>

### III. Gullible Agents

Though the Digital Eye does not seem to be an imminent danger, programs are much more likely to collude if one or more are “gullible”—advanced enough to react to competitors, but too simple to recognize when there is deadweight loss and that lowering prices would increase profits.

For example, a simple competitor-based algorithm—as provided by common e-marketplaces<sup>205</sup>—is highly gullible. It is, by definition, interdependent with its competitor. Whenever the competitor raises or lowers its price, so does this gullible agent. If a trained “persuasive” algorithm has such an agent as its only competitor, that persuasive agent would naturally learn to set monopolist prices. Indeed, there would be little difference in the data received by the persuasive agent than if it were a monopolist—that is, in direct control of both its market share and the market share of the gullible agent.

These gullible agents are similar to predictable agents. Indeed, whether a scenario with two colluding competitor-based algorithms is a Gullible Agent scenario or a Predictable Agent scenario depends only on whether the users intended for their algorithms to collude. In the Gullible Agent scenario, collusion is an accident; in the Predictable Agent scenario, it is not. While subtle, this difference is critical. Without intent, collusion by gullible agents circumvents even the FTC’s expanded antitrust stance.

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201. See Julien Perolat, Joel Z. Leibo, Vinicius Zambaldi, Charles Beattie, Karl Tuyls & Thore Graepel, *A Multi-Agent Reinforcement Learning Model of Common-Pool Resource Appropriation*, ADVANCES NEURAL INFO. PROCESSING SYS., 2017, at 1, 8.

202. See Brown & MacKay, *supra* note 28, at 110.

203. See, e.g., Bruno Salcedo, *Pricing Algorithms and Tacit Collusion 3* (Nov. 1, 2015) (Ph.D. dissertation, Pennsylvania State University), <https://perma.cc/ZN33-FSL7>.

204. See Natasha Jaques, Angeliki Lazaridou, Edward Hughes, Caglar Gulcehre, Pedro A. Ortega, DJ Strouse, Joel Z. Leibo & Nando de Freitas, *Social Influence as Intrinsic Motivation for Multi-Agent Deep Reinforcement Learning*, PROCS. ON MACH. LEARNING RSCH., 2019, § 1 (proposing a pro-social algorithm).

205. See *Amazon Automation*, *supra* note 37; *Walmart Repricer Overview*, *supra* note 49.

As such, gullible algorithms are a present threat to consumer welfare. They are anticompetitive, common, and—lacking intent—elude both traditional antitrust enforcement and the FTC’s newer approach.

#### A. Gullibility Is Anticompetitive

Scholars have noted how algorithms can amplify the effects of anticompetitive agreements,<sup>206</sup> but gullible algorithms are prone to cause supracompetitive pricing absent human agreement or intent. This holds true in a variety of markets, whether the gullible agents compete against other gullible agents or against sophisticated algorithms.

First, gullible agents are likely to collude when they compete against each other. Take, for example, the two runaway Amazon book sellers.<sup>207</sup> In this case, each rule-based algorithm set its price at a fixed proportion of the other, such that both of their prices were soon in the millions.<sup>208</sup> These programs colluded, albeit through ignorance and error rather than intention or agreement.<sup>209</sup> Certainly, this particular instance required no government intervention. The algorithms’ prices increased far beyond the point of profitability, and their “thinking” was obvious. However, if these programs had price ceilings—which the overwhelming number of available algorithms possess<sup>210</sup>—their behavior would have been significantly more concerning. The algorithms would have reached the high end of plausibly competitive prices and remained there. They would have been too simple to realize they formed a cartel, let alone be tempted to break it. The algorithms’ users could always intervene to undercut each other. But if it took nearly two months for either one of the Amazon booksellers to realize that their prices were approaching the millions,<sup>211</sup> users might never realize when their prices are at the high end of competitive plausibility. And even if they did notice, after a stable cartel had already been established, these users would have little incentive to deviate. At that point, there would be anticompetitive intent and Section 5 liability. But the Gullible Agent scenario creates plausible deniability

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206. Ezrachi & Stucke, *supra* note 35, at 249-50 (discussing the effects of retail price maintenance restrictions when using “pricing algorithms which automatically adapt retail prices to those of competitors” (quoting European Commission Press Release IP/18/4601, Antitrust: Commission Fines Four Consumer Electronics Manufacturers for Fixing Online Resale Prices (July 24, 2018))).

207. *See* Solon, *supra* note 34.

208. *See* Eisen, *supra* note 74.

209. *Id.*

210. *See, e.g., supra* notes 47-55 and accompanying text.

211. *See* Eisen, *supra* note 74 (reporting a pricing pattern that, when extrapolated, went from late February to April 18, 2011).

and an evidentiary nightmare—one that is worsened when the anticompetitive algorithm itself is offered so readily by the marketplace.<sup>212</sup>

Gullible agents are also prone to collude when they are competing against sophisticated, trained pricing algorithms. Scholarship has shown that pricing algorithms reach higher prices when a rule-based algorithm competes with a trained algorithm than when both algorithms are trained.<sup>213</sup> A contemporary trained algorithm—with current technology and no human intent to collude—can learn to manipulate the linear agents.<sup>214</sup> The sophisticated algorithm will be advantaged by many of the conditions that make it easier for machines to learn: near-immediate cause and effect,<sup>215</sup> little noise,<sup>216</sup> and linear relationships between variables.<sup>217</sup> In such an environment, even a simple trained model is likely to identify stable supracompetitive pricing strategies.<sup>218</sup> Yet, unlike the Amazon booksellers’ runaway pricing,<sup>219</sup> this algorithmic coordination can remain unnoticed by firms and law enforcement because the profit-maximizing trained algorithm will keep prices low enough that customers still pay.

Certainly, when gullible agents use competitor-based pricing, it is, by definition, impossible for their competitors to *avoid* influencing their prices. For the most common implementations of competitor-based pricing, the rule-based algorithms set their prices to always track their competitors’ prices by a fixed amount or percentage.<sup>220</sup> If all of a trained algorithm’s competitors use such rules, the world looks effectively the same to it as if it were a monopolist.<sup>221</sup> That is, all prices in the market instantly move toward the

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212. See, e.g., *Amazon Automation*, *supra* note 37; *Walmart Repricer Overview*, *supra* note 49.

213. See Wang et al., *supra* note 25, at 4-5.

214. See *id.* at 40.

215. Cf. Beining Han, Zhizhou Ren, Zuofan Wu, Yuan Zhou & Jian Peng, *Off-Policy Reinforcement Learning with Delayed Rewards*, PROCS. ON MACH. LEARNING RSCH., 2022, § 2.2 (discussing how delayed rewards can degrade learning of standard reinforcement-learning algorithms).

216. Jingkang Wang, Yang Liu & Bo Li, *Reinforcement Learning with Perturbed Rewards*, 2020 THIRTY-FOURTH AAAI CONF. ON A.I. 6202, 6202.

217. Aayush Ostwal, *Five Obstacles Faced in Linear Regression*, MEDIUM (Jan. 2, 2021), <https://perma.cc/WF6A-PC9W> (“Linear Regression is one of the most trivial machine algorithms.”).

218. See, e.g., Wang et al., *supra* note 25, at 21 fig. 3.

219. See Eisen, *supra* note 74.

220. See, e.g., *Repricer: Create a Strategy*, *supra* note 42 (Walmart); *Create a Pricing Rule*, *supra* note 42 (Amazon). Barring price floors and ceilings, this is the only option for competitor-based pricing provided by Walmart Marketplace and Amazon’s built-in algorithms. *Repricer: Create a Strategy*, *supra* note 42; *Amazon Automation*, *supra* note 37.

221. See, e.g., Wang et al., *supra* note 25, at 21 fig. 3 (demonstrating the ease with which such a trained algorithm learns monopolist behavior).

price the trained algorithm sets. The sophisticated algorithm is constrained only by market elasticity, just like a monopolist. As such, even the most basic trained algorithm will learn to act like a monopolist and bring all algorithms to monopolist or near-monopolist prices.

## B. Gullibility Is Common

The Gullible Agent scenario is possible in any industry with pricing algorithms. The nature of gullible agents is that they are simple to create: As demonstrated in the examples above and by the million-dollar Amazon booksellers, a few basic rules are sufficient. In industries where they are available, gullible agents appear very popular.<sup>222</sup>

The e-commerce market appears particularly susceptible, given the large quantity of smaller retailers and the availability of rule-based models in most major online markets.<sup>223</sup> In 2015, roughly one-third of the top 1,600 best-selling items on Amazon used competitor-based algorithmic pricing.<sup>224</sup> Given the increasing prevalence of pricing algorithms over the past decade—and that competitor-based algorithms remain the most popular option—it is likely that the proportion of potentially gullible agents has only increased.<sup>225</sup>

The number of gullible agents also extends beyond competitor-based models. Trained algorithms and sophisticated rule-based algorithms can also be gullible, depending on their own level of sophistication and that of their competitors. Researchers have made advanced trained models capable of decoding and manipulating other trained algorithms into increasing their prices.<sup>226</sup> Recall that gullibility means failing to recognize when lowering prices will increase profits and that these advanced models can learn what conditions will “trick” their competitors into not recognizing deadweight

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222. See, e.g., *id.* at 10-11.

223. See, e.g., *Amazon Automation*, *supra* note 37; *Walmart Repricer Overview*, *supra* note 49; REPRICER.COM, *supra* note 56.

224. See Chen et al., *supra* note 21, at 1340, 1344 tbl.2. The gullibility of these algorithms is harder to determine, though in many cases the algorithms tracked competitor prices precisely. *Id.* at 1345 figs. 14-17, 1346.

225. See Wang et al., *supra* note 25, at 9-10; see also *supra* notes 47-50 and accompanying text (describing the focus on simple competitor-based pricing algorithms in Walmart Marketplace’s built-in options); *supra* notes 51-55 and accompanying text (showing a similar focus in Amazon’s built-in algorithms); *supra* notes 56-60 and accompanying text (showing a similar focus by the third-party provider Repricer).

226. Luc Rocher, Arnaud J. Tournier & Yves-Alexandre de Montjoye, *Adversarial Competition and Collusion in Algorithmic Markets*, 5 NATURE MACH. INTEL. 497, 498 (2023).

loss.<sup>227</sup> As such, simple trained algorithms may be gullible or are likely to become gullible as the best available algorithms get better.

While these gullible agents appear common, their combined effect on markets is difficult to determine. But to the extent that Project Nessie worked because of the simplicity of competitors’ pricing algorithms, there alone the Gullible Agent scenario generated an estimated \$1 billion in additional profit for Amazon.<sup>228</sup>

### C. Gullibility Eludes Remedy

The Gullible Agent scenario is a present risk and does not require human intent. The simplicity of a gullible agent creates a high likelihood that moderately sophisticated algorithms will independently learn to manipulate it. Without human intent or agreement, the Sherman Act and the FTC Act are largely inapplicable, despite the potential for consumer exploitation on a massive scale.

#### 1. The free market

The free market is unlikely to resolve the problem on its own. If the algorithm users never discover their incidental collusion, they will not intentionally correct it. In this scenario, the persuasive agent is not necessarily designed to manipulate other algorithms, so it is entirely plausible that its users never intended to collude. It is similarly plausible that a gullible agent gets implemented without collusive human intent—firms have already used such algorithms and found themselves surprised by the results.<sup>229</sup>

Additionally, even if the algorithm users eventually recognize what occurred, both parties have the incentives and plausible deniability to maintain their collusion. That is, there would then be anticompetitive intent, but with minimal or no evidence. The sophisticated entity gets to set supracompetitive prices without being undercut. The gullible party may at some point recognize that it could make more money by lowering its price, but proving that a company had such knowledge is challenging.<sup>230</sup> The unpredictability of the persuasive algorithm makes this determination much more difficult than it

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227. At some point of increasing sophistication, the “gullible” agent can be more accurately described as choosing to ignore deadweight loss because it understands long-term planning. The scenario then becomes that of the Predictable Agent or Digital Eye. Both raise other challenges for antitrust enforcement, as discussed in previous scholarship. *See supra* notes 189-205 and accompanying text.

228. *See* Complaint [Public Redacted Version], *supra* note 4, at 121.

229. *See* Solon, *supra* note 34.

230. Even then that knowledge is not currently illegal, though it may create liability under the FTC’s expanded approach. *See infra* Part III.C.3.

was in the Predictable Agent scenario. This gives the gullible party little incentive to research, develop, and improve their algorithm—but antitrust enforcers will struggle to differentiate illegal intent from genuine ignorance.<sup>231</sup> Investigations would require challenging the motives behind complex business decisions on research and development investments.

## 2. The extended antitrust toolkit

As shown above, gullible agents can collude without human agreement, intent, or knowledge. Without evidence of agreement, the Sherman Act imposes no liability.<sup>232</sup> Under the “traditional view,” Section 5 has narrow standalone authority.<sup>233</sup> That authority is unlikely to apply in cases that lack anticompetitive intent, where a firm’s behavior—let alone mindset—is “in essence . . . identical to that of sellers in a competitive industry.”<sup>234</sup>

Under the FTC’s expanded approach, there could be antitrust liability if the Commission can show that price setting with gullible agents is a per se pernicious use of market power and tends to have anticompetitive effects.<sup>235</sup> But the FTC would likely struggle to identify a per se pernicious use of gullible agents. Without anticompetitive intent, the use of gullible agents is hardly coercive, abusive, deceptive, or predatory. Such labels generally apply to firms that exert excessive control over the market, not those that unintentionally give up control over their own price setting. As such, though gullible agents tend to have anticompetitive effects, the FTC’s sliding scale would require it to demonstrate that tendency to an extraordinarily high degree.<sup>236</sup> Construing the FTC’s sliding scale analysis to condemn methods that lack anticompetitive intent, provable or not, would also create tension with the restrictions from *Ethyl* and *Boise*.<sup>237</sup> Further, even where gullible and persuasive algorithms are

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231. *A Conversation with FTC Commissioner Andrew Ferguson Hosted by Alden Abbott*, *supra* note 162 (reporting now-FTC Chair Andrew Ferguson’s comments on how algorithms allow collusion such that “the collusion, at least the intentionality of the collusion, may not be super obvious”).

232. 15 U.S.C. § 1 (2014).

233. *See supra* notes 126-28 and accompanying text.

234. Turner, *supra* note 102, at 666.

235. *See* SECTION 5 POLICY STATEMENT, *supra* note 94, at 9.

236. *See id.* at 9-10 (explaining that a practice’s anticompetitive tendency can be evaluated in the aggregate along with other gullible agent users).

237. *Contrast id.*, with *Ethyl*, 729 F.2d 128, 139 (2d Cir. 1984) (requiring, absent tacit agreement, “some indicia of oppressiveness”), and *Boise Cascade Corp. v. FTC*, 637 F.2d 573, 576-77 (9th Cir. 1980) (requiring either “evidence of overt agreement” or tacit agreement shown by an actual “effect of fixing or stabilizing prices”). For a perspective that resolves these tensions by limiting Section 5 to cases involving anticompetitive intent, see notes 141-42 above and accompanying text.

deployed with the intention to collude—and so create antitrust liability under the FTC’s expanded approach—there are good reasons to suspect that the FTC Act would be an inefficient and undesirable solution.

First, decoding linear systems is “trivial” in machine learning,<sup>238</sup> and it is likely to happen with any trained algorithm. This suggests that expansive technical limitations would be required to prevent a persuasive agent from decoding its competitors. A machine learning algorithm would have to be blinded to the prices of its competitors to incorporate that information into its learning, which would remove many of the substantial pro-competitive efficiencies that pricing algorithms can provide.<sup>239</sup> Second, even blinded, sophisticated algorithms would still be likely to “persuade” gullible agents. The difficulty of blinding AI to specific kinds of data is well-documented—studies have shown AI can recreate censored information from much more challenging multivariable nonlinear systems.<sup>240</sup> Third, should a gullible algorithm be sufficiently simple, it will not be possible to prevent competitors from influencing it: If a firm uses a competitor-based algorithm,<sup>241</sup> supracompetitive prices would be unavoidable so long as their competitor’s pricing algorithm involves even a basic assessment of the profitability of alternative prices.

It is possible to train algorithms in such a way that “punishes” them when they influence other algorithms.<sup>242</sup> However, this approach would leave enforcers with the difficult task of distinguishing between raising prices to attempt collusion and raising prices to determine whether market elasticity is lower than expected. This approach would also punish firms that fail to make that determination correctly.<sup>243</sup> Drawing such a distinction requires enforcement agencies and firms to determine the rationale behind AI decisions—a notoriously difficult technical endeavor.<sup>244</sup> It is unrealistic to expect that such an analysis can be performed effectively.

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238. See Ostwal, *supra* note 217.

239. See *supra* notes 30-31 and accompanying text.

240. See, e.g., Judy Wawira Gichoya et al., *AI Recognition of Patient Race in Medical Imaging: A Modeling Study*, 4 LANCET DIGIT. HEALTH 406, 412-13 (2022).

241. See, e.g., Solon, *supra* note 34.

242. See Jaques et al., *supra* note 204, §§ 1, 3-4.1 (proposing a trained algorithm that is motivated by its level of causal influence on other agents). *But see* PHIL C. NEAL ET AL., REPORT OF THE WHITE HOUSE TASK FORCE ON ANTITRUST POLICY (1968) (arguing that antitrust law “cannot order the several firms to ignore each other’s existence”), reprinted in 2 ANTITRUST L. & ECON. REV. 11, 22-23 (1968-1969).

243. This requirement to check the decisions of algorithms would also deter firms from using them to rapidly respond to market fluctuations, reducing the procompetitive potential of pricing algorithms to capture market inefficiencies.

244. See Castelveccchi, *supra* note 64.

Attempting to regulate the persuasive agent’s behavior also escalates Turner’s concerns.<sup>245</sup> The persuasive agent in this scenario is using legally available information—including the predictability of the gullible agent—to make rational market decisions. At no point does the persuasive agent “sacrifice” short-term profitability to maintain supercompetitive prices.<sup>246</sup> In contrast, the gullible agent effectively enforces its faux agreement. If the persuasive agent drops its prices, the gullible agent automatically and immediately follows. But if the gullible agent drops its prices, the persuasive agent merely includes that information as a part of a larger price calculus of “impersonal market facts.”<sup>247</sup> The persuasive agent’s behavior is essentially what Turner has described as “that of sellers in a competitive industry”—taking the gullible agent’s “probable decisions” as “impersonal market facts.”<sup>248</sup> While Posner has argued that businesses know when they behave noncompetitively<sup>249</sup> and that a leading seller who refuses to collude will not sustain noncompetitive prices,<sup>250</sup> gullible agents usurp both assumptions.

As such, the Gullible Agent scenario is present and seemingly immune to the existing antitrust toolkit. It may be intuitive to further expand the FTC Act to encompass persuasive agents: Antitrust tends to focus on sophisticated parties, as seen in the FTC’s approach to Project Nessie.<sup>251</sup> But doing so in the Gullible Agent scenario clashes with technical realities and established antitrust policy.<sup>252</sup> It would likely require substantial restrictions and offer limited results.

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245. See Turner, *supra* note 102, at 666.

246. See Vestager, *supra* note 88.

247. See Turner, *supra* note 102, at 666.

248. *Id.*

249. Posner, *supra* note 85, at 1592 (“Tacit collusion is not an unconscious state. . . . [G]iven the tension between sales and financial executives that characterizes most corporations, the question whether to collude tacitly will be thrust upon management constantly. The sales people will argue for offering discounts to lure away rivals’ customers, for varying prices promptly as conditions of demand and cost change, for reducing prices to utilize idle capacity or to exploit locational advantages, and for other competitive, sales-increasing tactics; and, whenever they do, management will have to balance their claims against the advantages of securing or maintaining an understanding with the company’s rivals to limit price competition.”).

250. *Id.* (“If [the oligopolist] is a leading seller—and a rule against tacit collusion would be invoked only against the leading sellers in a market—his refusal to accede to an understanding on prices will make it impossible for the other firms to maintain noncompetitive prices. . . .”).

251. See, e.g., Complaint [Public Redacted Version], *supra* note 4 (targeting Amazon instead of its competitors).

252. See Turner, *supra* note 102, at 666.

### 3. Other proposals

There have been many other proposals on how to address collusion from pricing algorithms, but none offer a sufficient remedy here. Proposals for tailored remedies<sup>253</sup> or novel investigative techniques<sup>254</sup> do not help with behavior beyond the scope of existing regulations. The FTC might attempt to treat algorithmic interactions as agreements in restraint of trade,<sup>255</sup> but gullible agent users lack the intent to form agreements.<sup>256</sup> Cooperative norm-setting efforts from the FTC could be an effective, low-downside method for encouraging large stakeholders—such as Amazon and Walmart—to modify the competition-based algorithms they offer to retailers.<sup>257</sup> But without a legal basis for pursuing gullible agents, these efforts would rely on the amicability of the companies and only indirectly address gullible agents created by individuals or small firms.

Proposed legislation would require users to disclose where and how they are using pricing algorithms and would presume an agreement where competitors share non-public, competitively sensitive data through a pricing algorithm.<sup>258</sup> But the Gullible Agent scenario does not involve any private disclosure of information. More disclosure may help the Department of Justice (DOJ) and the FTC identify anticompetitive effects, but it does not address the Gullible Agent scenario’s lack of anticompetitive intent.<sup>259</sup>

Another proposal is to treat pricing algorithms as announcements under Section 5 of the FTC Act.<sup>260</sup> Public announcements can be understood as “the conveyance of information by a firm or one of its employees using a medium

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253. See, e.g., Francisco Beneke & Mark-Oliver Mackenrodt, *Remedies for Algorithmic Tacit Collusion*, 9 J. ANTITRUST ENFT 152, 164-75 (2020) (recommending fines and other remedies once antitrust breach has been established).

254. See, e.g., Cary Coglianese & Alicia Lai, *Antitrust by Algorithm*, 2 STAN. COMPUTATIONAL ANTITRUST 1, 8 (2022) (recommending that enforcement agencies use machine learning to identify collusion).

255. Michal S. Gal, *Algorithms as Illegal Agreements*, 34 BERKELEY TECH. L.J. 67, 98-99 (2019).

256. *Id.* at 107 (“Engaging in an agreement requires the intent to do so.”). While Michal Gal explores different degrees of programmer awareness, *id.* at 108, gullible agent users can lack any awareness of their anticompetitiveness, see, e.g., Solon, *supra* note 34.

257. See Mehra, *supra* note 29, at 1369-73 (suggesting that the FTC should shape industry behavior through a flexible blend of dialogue, regulation, and norm generation).

258. Preventing Algorithmic Collusion Act of 2024, S. 3686, 118th Cong. §§ 5(a)(1)-(2), 6(a) (2024), <https://perma.cc/5BLR-UV7M>; see also Klobuchar, *Colleagues Introduce Antitrust Legislation to Prevent Algorithmic Price Fixing*, U.S. SENATOR AMY KLOBUCHAR (Feb. 2, 2024), <https://perma.cc/B9PJ-S8LB> (interpreting the Act).

259. See *supra* notes 140-48 and accompanying text (discussing how, even under a broad reading of Section 5, antitrust law likely permits interdependence where anticompetitive intent is absent).

260. See Mazumdar, *supra* note 112, at 475-87.

that is widely accessible to individuals outside of the firm.”<sup>261</sup> While public announcements are not necessarily anticompetitive, they can be considered invitations to collude<sup>262</sup> and therefore fall within historical applications of Section 5.<sup>263</sup>

Many of the simple rule-based algorithms in use are explicitly public—Amazon<sup>264</sup> and Walmart<sup>265</sup> have “announced” their rules online for any competitor to see. Sufficiently simple nonpublic algorithms can be similarly transparent due to the predictability of their pricing decisions.<sup>266</sup> By treating public or readily decipherable algorithms as invitations to collude, the FTC may already have authority to prevent gullible pricing agents from flooding vulnerable markets.<sup>267</sup>

However, this approach is bound by specific constraints. To prosecute an announcement under Section 5, the FTC would have to show an anticompetitive intent or effect.<sup>268</sup> As discussed previously, this is particularly challenging given that the algorithms are used by thousands of small vendors. This approach would also create significant uncertainty on the part of the algorithm users. Concerns about regulating tacit collusion often come down to clarity over what is and is not permissible behavior.<sup>269</sup> While the

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261. Joseph E. Harrington, Jr., *Collusion in Plain Sight: Firms’ Use of Public Announcements to Restrain Competition*, 84 ANTITRUST L.J. 521, 523 (2022).

262. See, e.g., *Valassis Commc’ns, Inc.*, 141 F.T.C. 247, 249-52 (2006) (finding an invitation to collude where a firm used a public earnings call to describe pricing and customer-allocation plans conditioned on its rival’s reciprocal conduct).

263. SECTION 5 POLICY STATEMENT, *supra* note 94, at 12 n.71.

264. *Amazon Automation*, *supra* note 37; *Amazon Match Price*, *supra* note 54.

265. *Walmart Repricer Overview*, *supra* note 49.

266. See EZRACHI & STUCKE, *VIRTUAL COMPETITION*, *supra* note 12, at 61-62 (describing the increase in transparency under the Predictable Agency scenario); *Pricing Algorithms: Economic Working Paper on the Use of Algorithms to Facilitate Collusion and Personalised Pricing* 4 (Competition & Mkts. Auth., Working Paper No. CMA94, 2018), <https://perma.cc/Z6KX-5LWZ> (discussing how the predictable pricing algorithms may “signal [their] intentions and make it easy for competitors to work out what is going on”).

267. See Mazumdar, *supra* note 112, at 475-87 (arguing that treating algorithms as announcements would allow the FTC Act to regulate pricing algorithms more generally); see also Kai-Uwe Kühn & Steven Tadelis, *The Economics of Algorithmic Pricing: Is Collusion Really Inevitable?* 23 (Dec. 2018) (unpublished manuscript), <https://perma.cc/8VA4-UDE2> (suggesting that current antitrust policy has already prevented some companies from deploying more easily decipherable algorithms).

268. See *Ethyl*, 729 F.2d 128, 139 (2d Cir. 1984) (requiring “some indicia of oppressiveness . . . such as (1) evidence of anticompetitive intent . . . or (2) the absence of an independent legitimate business reason for [the] conduct”); *Boise Cascade Corp. v. FTC*, 637 F.2d 573, 577 (9th Cir. 1980) (requiring, absent evidence of agreement, that the FTC demonstrate an actual “effect of fixing or stabilizing prices”).

269. See Turner, *supra* note 102, at 666.

“announcement” lens might provide a clear determination when Amazon publicly announces competitor-based pricing rules,<sup>270</sup> small vendors are less capable of the sophisticated economic analysis needed to determine whether their individual use of the rules would be anticompetitive.<sup>271</sup> The FTC could instead hold Amazon liable, but Amazon would then be forced to scrutinize to which of its vendors it can offer competitor-based pricing. Alternatively, Amazon could stop offering these pricing rules entirely and so deprive the market of the competitive advantages of pricing algorithms.

Treating pricing algorithms as announcements would also give pricing algorithms higher scrutiny but would not itself render them unlawful. Insofar as the FTC and DOJ lack evidence of intent, any collusive conduct would remain permissible under Section 5.<sup>272</sup>

Finally, it strains credulity to interpret accidental gullibility as an announcement. Many of the vendors who employ gullible agents are merely using an option the market owner offered them.<sup>273</sup> They are not intending to collude, much less intending to signal their interest in forming a conspiracy.

#### IV. Duty to Discern

Many of the challenges outlined in Part III above can be avoided by focusing on the gullible agents instead of the persuasive ones. Increasing the complexity of the gullible algorithms, even by a relatively small amount, can make collusion much more technically difficult to achieve.<sup>274</sup> If algorithms

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270. *Amazon Match Price*, *supra* note 54.

271. The difficulty of such economic analysis is well noted. *See, e.g.*, Thomas B. Leary, *Efficiencies and Antitrust: A Story of Ongoing Evolution*, FTC (Nov. 8, 2002), <https://perma.cc/ZA56-NBJ6> (“[T]here really are serious problems associated with any effort to demonstrate rigorously that potential efficiencies outweigh potential anticompetitive effects.”); Michael R. Baye & Joshua D. Wright, *Is Antitrust Too Complicated for Generalist Judges? The Impact of Economic Complexity and Judicial Training on Appeals*, 54 J.L. & ECON. 1, 2 (2011); Rohit Chopra & Lina M. Khan, *The Case for “Unfair Methods of Competition” Rulemaking*, 87 U. CHI. L. REV. 357, 361 (2020).

272. *See supra* Part II.A (arguing that anticompetitive intent is effectively necessary for the application of current antitrust law, even under the expanded view of the FTC Act).

273. *See, e.g., Amazon Match Price*, *supra* note 54; *Walmart Repricer Overview*, *supra* note 49.

274. *See* Wang et al., *supra* note 25, at 18-21 (demonstrating the dramatic difference in learning dynamics between two Q-learning agents and between a Q-learning agent and a rule-based agent); Ulrich Schwalbe, *Algorithms, Machine Learning, and Collusion*, 14 J. COMPETITION L. & ECON. 568, 590-92 (2018) (“[C]oordinated behavior among algorithms is possible but not as rapid, easy, or even inevitable as often assumed by legal scholars. . . . Although recent literature on the impending danger of algorithmic collusion often refers to complex algorithms . . . , the collusive behavior of such price-setting algorithms . . . is illustrated using basic deterministic rules such as simple leader-follower or price-matching ones.” (citations omitted)); Gautier et al., *supra* note 20, at 418-20 (reviewing findings that autonomous collusion is theoretically  
*footnote continued on next page*

engage in some more-than-nominal analysis of whether to independently lower prices—that is, to “discern” whether they are at a supracompetitive price—the likelihood of collusion decreases dramatically.<sup>275</sup> As such, gullible agents can be regulated by acknowledging the inherent danger in overly simplistic pricing algorithms and requiring firms that decide to use pricing algorithms to meet a reasonable standard of care in avoiding algorithms that are overly gullible.

#### A. Gullibility as Hackability

As discussed above, it may seem intuitive from the antitrust perspective to address the Gullible Agent scenario by scrutinizing the conduct of the more sophisticated parties and their persuasive algorithms. But the high—sometimes inherent—interdependence created by gullible agents suggests that the scenario more closely resembles a negligence problem. That is, if interdependence is a natural consequence of gullibility,<sup>276</sup> then the developers of gullible agents look less like manipulated bystanders and more like manufacturers whose designs foreseeably harm consumers with unreasonable frequency. The corresponding solution, then, is a duty of care requiring firms that use competitor-based algorithmic pricing to ensure their programs are not unreasonably prone to follow supracompetitive prices.

Duties are justified when agents choose an endeavor known to carry risk,<sup>277</sup> and choosing to use a pricing algorithm carries additional risk. When firms with manual pricing use even simple strategies, human decisionmaking introduces a complex system of intuitive, implicit checks. That is, when humans employ “simple” pricing strategies, they still react when the strategy goes obviously awry. A human would not match a competitor’s price increase

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possible, but limited in practice); Ryan Lowe, Yi Wu, Aviv Tamar, Jean Harb, Pieter Abbeel & Igor Mordatch, *Multi-Agent Actor-Critic for Mixed Cooperative-Competitive Environments*, 30 ADVANCES NEURAL INFO. PROCESSING SYS. 6380, 6381-82 (2017) (reviewing the difficulty of achieving cooperation between even basic Q-learning models). Some design choices can make complex algorithms more capable of collusion, see John Asker, *Artificial Intelligence and Pricing: The Impact of Algorithm Design* 38 (Nat’l Bureau of Econ. Rsch., Working Paper No. 28535, 2021), but suggest human intent that would turn the scenario into that of the Predictable Agent, see *supra* notes 185-94 and accompanying text.

275. See *supra* note 274.

276. See *supra* Part III.A.

277. See David Owen, *Duty Rules*, 54 VAND. L. REV. 767, 778 (2001) (“In general, actors are morally accountable only for risks of harm they do or reasonably should contemplate at the time of acting . . .”).

from \$100 to \$23,000,000.<sup>278</sup> They would recognize the opportunity to capture more of the market and lower the price. A person cannot credibly claim that they thought raising their price by over twenty-two million percent was competitive behavior. Because algorithms do not automatically come with an understanding of “competition” or “common sense,” they carry an inherent anticompetitive risk that human pricing does not. As such, liability is reasonable for those who choose to use pricing algorithms but fail to take the necessary steps to mitigate that chance of harm.

Established duties of care can illustrate how this minimum standard for pricing algorithms might operate. Duties of care that evolve with technology, for example, are already standard in medicine,<sup>279</sup> automobile safety,<sup>280</sup> product liability,<sup>281</sup> and many other domains.<sup>282</sup> But emerging scholarship and legislation are already developing around an even more analogous problem: weak cybersecurity. These proposals suggest liability for developers whose programs are unreasonably vulnerable to control by malicious hackers.<sup>283</sup> They similarly grapple with more specific challenges, such as how to set a predictable standard of care given that the capabilities of hacker-persuaders can advance unpredictably and vary greatly. Understanding gullibility as hackability generalizes the problem as one of software manipulation and offers an existing framework to build upon.

The policy benefits of creating this duty are substantial. A duty to avoid unreasonably gullible pricing algorithms would sidestep technical challenges<sup>284</sup> and alleviate Turner-esque concerns.<sup>285</sup> Many firms already

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278. See Solon, *supra* note 34 (explaining that Profnath dropped the price of its book to \$106.25 after realizing the book’s price reached over \$23 million using Amazon’s algorithmic pricing).

279. A. Michael Froomkin, Ian Kerr & Joelle Pineau, *When AIs Outperform Doctors: Confronting the Challenges of a Tort-Induced Over-Reliance on Machine Learning*, 61 ARIZ. L. REV. 33, 51 (2019).

280. Tania Leiman, *Law and Tech Collide: Foreseeability, Reasonableness and Advanced Driver Assistance Systems*, 40 POL’Y & SOC’Y 250, 261 (2021).

281. James Boyd & Daniel E. Ingberman, *Should “Relative Safety” Be a Test of Product Liability?*, 26 J. LEGAL STUD. 433, 433-35 (1997).

282. See Froomkin, Kerr & Pineau, *supra* note 279, at 51-52 (“U.S. tort law recognizes that technology changes what is possible and reasonable, and thus the general standard of care for professions and trades may change too.”).

283. BIDEN ADMIN., NATIONAL CYBERSECURITY STRATEGY 20-21 (2023), <https://perma.cc/HWV6-ZFS2>; see also Alan Butler, *Products Liability and the Internet of (Insecure) Things: Should Manufacturers Be Liable for Damage Caused by Hacked Devices?*, 50 U. MICH. J.L. REFORM 913, 918 (2017) (arguing the merits of extending product liability to digital hacks).

284. See *supra* notes 233-39.

285. See *supra* notes 240-45.

make non-gullible agents,<sup>286</sup> and it will likely be much easier for a firm to determine whether a basic algorithm meets this minimum standard than to conduct economic analysis on the effect of a sophisticated program.<sup>287</sup> For one, the former analysis is scalable. An algorithm’s anticompetitive effect depends on individual factors such as market share and competitor behavior. This limits the development of industry norms for assessing anticompetitive effect like those for assessing software vulnerability.<sup>288</sup>

Additionally, this duty of care could ease the enforcement difficulties raised by the Predictable Agent scenario, whose regulation under antitrust law requires a showing of anticompetitive intent.<sup>289</sup> Consider a firm that intentionally creates a simple, predictable agent to elicit supracompetitive prices. The firm possesses anticompetitive intent, but proving that intent can be challenging. A standard of care would avoid this enforcement problem by discouraging unreasonably manipulable algorithms regardless of their users’ intent or knowledge.

### B. Crafting the Duty

The most straightforward approach to establishing this duty would be to locate it in the FTC’s existing Section 5 consumer protection authority.<sup>290</sup> Indeed, that authority is already used to enforce a similar duty to properly secure data.<sup>291</sup> However, the FTC’s consumer protection authority has been consistently construed as a prohibition on unfair acts in direct relation to the consumer.<sup>292</sup> Understanding the use of gullible agents as an unfair practice

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286. See Part I.A (describing sales-based pricing, time-based pricing, and trained algorithms).

287. Recall the challenges of such analysis, discussed in notes 268-71 above and accompanying text.

288. *Cybersecurity Standards and Frameworks*, IT GOVERNANCE, <https://perma.cc/4S2V-9SJK> (archived Sept. 25, 2025).

289. See *supra* notes 185-92 and accompanying text.

290. 15 U.S.C. § 45. Distinct from the “unfair methods of competition” Section 5 authority discussed thus far, the Wheeler-Lea Act amended Section 5 to include the consumer protection authority to prohibit “unfair or deceptive acts or practices.” Pub L. No. 75-447, § 3, 52 Stat. 111, 111 (1938).

291. William McGeeveran, *The Duty of Data Security*, 103 MINN. L. REV. 1135, 1148-52 (2019) (describing the FTC’s enforcement of a “duty of data security” through its Section 5 consumer protection authority).

292. See Margaret Krawiec, Ivan Schlager, Neepa Mehta, Keyawna Griffith & Lotus Ryan, *FTC Trends in Consumer Protection*, 31 LOY. CONSUMER L. REV. 225, 236-37, 240-41, 245-46, 250, 254-55 (2019) (discussing the FTC’s consumer protection focus on financial fraud, online scams, consumer data security, illegal robocalls, and deceptive health care advertising); Daniel J. Solove & Woodrow Hartzog, *The FTC and the New Common Law of Privacy*, 114 COLUM. L. REV. 583, 638-40 (2014) (suggesting that the FTC’s consumer protection cases are generally brought against practices that prevent consumers from effective decisionmaking). See generally Khan, Levine & Nguyen, *supra* note 153  
*footnote continued on next page*

merely because it “causes or is likely to cause substantial injury to consumers”<sup>293</sup> would dramatically extend the FTC’s consumer protection authority with little basis.

Consequently, creating a duty to use non-gullible algorithms would likely require legislative action. To utilize the FTC’s expertise in bringing claims for problematic data security practices,<sup>294</sup> legislators might create the duty by amending the FTC Act. Legislative momentum could support such a change. In 2024, Senator Amy Klobuchar introduced a bill that would require companies to disclose whether they are using pricing algorithms.<sup>295</sup> Congress could similarly introduce a standard of care akin to the Biden Administration’s proposed liability framework for unacceptably hackable systems.<sup>296</sup>

While state legislation could also create a private right of action,<sup>297</sup> such legislation would dramatically increase the number of potential enforcers for a novel duty.<sup>298</sup> Additionally, limiting enforcement to the FTC would not require the agency to individually prosecute thousands of small retailers. This duty to discern could implicate both the users of gullible algorithms and the algorithm vendors who provide them. These central suppliers, then, could be encouraged to limit the gullibility of many users’ algorithms with relatively little administrative expense.

In setting the metes and bounds of the duty itself, lessons can be taken from proposals for a hackability standard,<sup>299</sup> the FTC’s consumer protection data security claims,<sup>300</sup> and general tort law. For example, any duty to avoid

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(discussing the FTC’s recent use of its consumer protection authority to regulate user data collection and manipulative design tactics).

293. 15 U.S.C. § 45(n).

294. Solove & Hartzog, *supra* note 292, at 650-56.

295. See Preventing Algorithmic Collusion Act, S. 3686, 118th Cong. § 6(a) (2024), <https://perma.cc/5BLR-UV7M>.

296. BIDEN ADMIN., *supra* note 283, at 20-21 (“Companies . . . must . . . be held liable when they fail to live up to the duty of care they owe consumers, businesses, or critical infrastructure providers.”).

297. Henry N. Butler & Joshua D. Wright, *Are State Consumer Protection Acts Really Little-FTC Acts?*, 63 FLA. L. REV. 163, 165 (2011) (discussing the creation of state-level “Little-FTC Acts,” which were primarily enforced by private plaintiffs).

298. See *id.* at 166 (summarizing arguments over the merits of private enforcement of Little-FTC Acts).

299. See, e.g., Stephen E. Henderson & Matthew E. Yarbrough, *Suing the Insecure?: A Duty of Care in Cyberspace*, 32 N.M. L. REV. 11, 11, 14-21 (2002); Michael L. Rustad & Thomas H. Koenig, *The Tort of Negligent Enablement of Cybercrime*, 20 BERKELEY TECH. L.J. 1553, 1580 (2005).

300. McGeveran, *supra* note 291.

gullible price setting must be based on preventable risk.<sup>301</sup> As discussed in Subpart A above, the technology industry offers deep experience in crafting cybersecurity standards to appropriately balance risk minimization and compliance costs.<sup>302</sup> Such standards may be used as probative, but not dispositive, evidence that reasonable care was taken to avoid gullibility.<sup>303</sup> In this manner, legislators and courts may craft an effective and balanced standard.

### C. Answering Objections

Three objections to instituting a duty of care appear particularly salient. First, a duty of care might be overly restrictive and disincentivize procompetitive uses of pricing algorithms.<sup>304</sup> Second, a duty of care might encourage sellers to use third-party algorithms and thereby raise market prices by centralizing algorithmic decisionmaking. Third, the cutoff for “gullibility” may be challenging to assess predictably. Ultimately, however, these objections appear less concerning and more manageable than those of alternative solutions.<sup>305</sup>

*Disincentivizing Beneficial Algorithms.*—One downside of instituting a standard of care is that it might disincentivize less sophisticated companies from using pricing algorithms. This would prevent those companies from minimizing certain market inefficiencies.<sup>306</sup> A standard of care could also hurt competition if algorithms help smaller companies compete with larger ones.<sup>307</sup>

Decreased algorithm adoption, however, is unlikely given the current state of gullible pricing algorithms. The prevalence of gullible algorithms appears to come largely from the ease with which large marketplaces make them available,<sup>308</sup> and those companies could be held responsible for providing algorithms that violate the duty of care. As such, it is up to these sophisticated

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301. Rustad & Koenig, *supra* note 299, at 1587 (arguing the same for a computer security standard of care).

302. See *Cybersecurity Standards and Frameworks*, *supra* note 288.

303. See Robert H. Heidt, *Damned for Their Judgment: The Tort Liability of Standards Development Organizations*, 45 WAKE FOREST L. REV. 1227, 1259 n.129 (2010) (describing common treatment of industry standards in tort law).

304. See *supra* note 243 and accompanying text.

305. See *supra* Part III.C.

306. See *supra* notes 30-31 and accompanying text.

307. See Chen et al., *supra* note 21, at 1347 (finding that Amazon was a more dominant seller of Amazon products when its competitors did not use pricing algorithms). The causality here, however, is likely flipped. That is, those who are already more sophisticated, serious competitors of Amazon tend to use pricing algorithms more.

308. See *supra* Part I.A.

entities whether to build less gullible algorithms or to cease offering built-in pricing algorithms. Since online marketplaces often profit directly from the size and frequency of transactions,<sup>309</sup> online marketplaces are incentivized to provide pricing algorithms if those algorithms (1) increase sales and (2) do not create an intolerable legal risk. Given that a standard for gullibility can be fairly predictable,<sup>310</sup> requiring non-gullibility appears unlikely to deter procompetitive algorithms.

*Increasing Hub-and-Spoke Risks.*—Another effect of a standard of care is that those less sophisticated companies will be more likely to use an upstream algorithm supplier. Non-gullible algorithms are more difficult to create, so a prohibition on gullible algorithms may push sellers to outsource the development of their programs. Upstream suppliers can create a more homogeneous set of algorithms, and similar algorithms are more likely to collude.<sup>311</sup> This collusion could take the form of the more manageable Hub-and-Spoke scenario, but it could also result in unintended collaboration between two sophisticated algorithms. While the Digital Eye is currently not technically feasible,<sup>312</sup> similar algorithms are more likely to “understand” each other.<sup>313</sup>

However, the algorithm market is likely highly centralized already, with many online retailers, at least, using the premade programs offered by their marketplace.<sup>314</sup> While a duty of care might prevent the pricing algorithm market from decentralizing in the future, preventing agents as gullible as pure competitor matchers is a low bar, especially for third-party algorithm suppliers.<sup>315</sup> It is also largely theoretical that centralizing the algorithm marketplace might make the Digital Eye more feasible. While similar algorithms may be more likely to understand each other, the notion that this risk factor could trigger any sort of tipping point is largely speculative.

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309. See, e.g., *What Is Walmart Marketplace?*, WEBFX, <https://perma.cc/A957-B3DP> (archived Sept. 25, 2025) (discussing Walmart Marketplace’s referral fee).

310. The predictability of such a standard is discussed in notes 318-28 below and accompanying text.

311. See EZRACHI & STUCKE, *VIRTUAL COMPETITION*, *supra* note 12, at 79.

312. See Ezrachi & Stucke, *supra* note 148, at 208; Gautier et al., *supra* note 20, at 415. For discussions of the challenges in reaching cooperation between sophisticated pricing algorithms, see note 274 above.

313. EZRACHI & STUCKE, *VIRTUAL COMPETITION*, *supra* note 12, at 79.

314. See, e.g., *Amazon Match Price*, *supra* note 54; *Walmart Repricer Overview*, *supra* note 49.

315. For examples of third-party pricing algorithm suppliers, see NEUROPRICE, <https://perma.cc/T3RL-L7VX> (archived Sept. 25, 2025); STREETPRICER, <https://perma.cc/N4VB-ECKZ> (archived Sept. 25, 2025); and SYMSON, <https://perma.cc/DNG3-8Z2S> (archived Sept. 25, 2025).

*Blurring Gullibility.*—The third and most fundamental concern is whether gullibility can be determined predictably. As discussed in Subpart A above, setting adaptable technical standards is not a new challenge, and hacking liability is an apt comparison. But this challenge still needs to be overcome, and gullibility needs to be identifiable for it to create liability.

While much of this Note has focused on gullible agents as price-matching algorithms, matched prices are not a dispositive indicator. Just as matched prices can mimic a monopoly, they can also mimic perfect competition.<sup>316</sup> Furthermore, focusing on the outcome of conduct, rather than the conduct itself, runs contrary to the fundamental principles laid out in *Ethyl*.<sup>317</sup> While the duty to discern would operate outside of antitrust law and *Ethyl*'s limits, the need for transparency and fairness to firms would remain.

Gullible agents, then, could be understood as algorithms that react to competitors but cannot respond to deadweight loss. For algorithms that do not check for deadweight loss, like most rule-based algorithms, this is a simple test. However, given the opaqueness of trained algorithms,<sup>318</sup> determining whether they recognize deadweight loss will likely require experimentation. It is also likely that a trained algorithm will recognize deadweight loss in some situations and not others. Sufficiently sophisticated competing algorithms can determine those blind spots and exploit them.<sup>319</sup>

As such, the margins of “gullibility” can be blurry, but a conservative classification would give firms a predictable legal standard while largely eliminating the risk from gullible agents. If gullibility is defined solely as not checking for deadweight loss, the standard would be perfectly predictable while still capturing nearly all of the algorithms currently available on Amazon, Walmart Marketplace, and Repricer.<sup>320</sup> And everything not captured would be significantly less gullible. The gulf between the gullibility of a competitor-based rule and of even a rudimentary trained program should not be understated. A “simple” trained algorithm might rely on decodable heuristics, but it is still far more complex than a rule-based agent.<sup>321</sup>

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316. See Nathalie Berta, Ludovic A. Julien & Fabrice Tricou, *On Perfect Competition: Definitions, Usages and Foundations*, 63 CAHIERS D'ÉCONOMIE POLITIQUE 7, 10-12 (2012).

317. See *Ethyl*, 729 F.2d 128, 138 (2d Cir. 1984).

318. See Castelveccchi, *supra* note 64.

319. See Rocher et al., *supra* note 226, at 498-99, 501 fig. 3 (demonstrating, in a simplified simulation, how an algorithm can learn the policies of three different Q-learning competitors to identify the best price sequence).

320. See *supra* Part I.A.

321. See also Wang et al., *supra* note 25, at 18-21 (demonstrating the dramatic difference in learning dynamics between two Q-learning agents and between a Q-learning agent and a rule-based agent).

Furthermore, the evidence of gullible trained algorithms has been from simplified simulated environments.<sup>322</sup>

While the standard for what is considered “gullible” will shift as persuasive algorithms improve, creating a simplified gullibility standard that only punishes the most egregious algorithms could still dramatically reduce the risk of collusion.<sup>323</sup> Algorithms that naively track competing prices are extraordinarily gullible. Competing algorithms need to be sophisticated in order not to reach supracompetitive prices when facing such gullible competitors.<sup>324</sup> In contrast, algorithms that experiment and respond to changes in profit require more sophisticated “persuasion.”<sup>325</sup> Such algorithms can identify some instances where lower prices can increase short-term profits, so a persuasive agent would have to be adaptive enough to identify and exploit competitors’ blind spots.<sup>326</sup> Finally, algorithms with shifting policies via machine learning tend to be less gullible still.<sup>327</sup> When competing against such an algorithm, a persuasive agent could test collusive behavior that is unsuccessful but would have been successful at a different time when its competitor had a different policy. When multiple adaptive algorithms are present, their collusive attempts are likely to “miss” each other. As unsuccessful collusive attempts are costly, decreasing the likelihood of success can have a dramatic effect on the odds of collusion occurring.

A separate challenge in classifying gullibility is that an advanced AI might learn that acting like a gullible agent maximizes its profits. This would be technically difficult. For one, such behavior would require synchronous

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322. See *supra* Part I.A.

323. See *supra* note 274 and accompanying text.

324. See *supra* text accompanying notes 241-42; see also, e.g., Solon, *supra* note 34 (discussing the two runaway Amazon booksellers).

325. See Arnoud V. den Boer, Janusz M. Meylahn & Maarten Pieter Schinkel, *Artificial Collusion: Examining Supracompetitive Pricing by Q-Learning Algorithms* 37 (Tinbergen Inst., Discussion Paper No. TI 2022-067/VII, 2022) (“Most existing well-performing algorithms learn to respond optimally to the environment that they are in, and will not easily converge to an action that can be improved upon.”). For examples of such dynamic pricing algorithms, see Yong Zhang, Francis Y.L. Chin & Hing-Fung Ting, *Online Pricing for Bundles of Multiple Items*, 58 J. GLOB. OPTIMIZATION 377, 381-82 (2014); and J. Michael Harrison, N. Bora Keskin & Assaf Zeevi, *Bayesian Dynamic Pricing Policies: Learning and Earning Under a Binary Prior Distribution*, 58 MGMT. SCI. 570, 574 (2012).

326. At the point where the more simplistic algorithm can “recognize” that the long-term profits of colluding outweigh the profits from defecting, the scenario becomes that of the Predictable Agent or the Digital Eye. Both raise other challenges for antitrust enforcement, as discussed in prior work. See *supra* notes 186-203 and accompanying text.

327. See Wang et al., *supra* note 25, at 18-21 (demonstrating the difficulty in achieving cooperation between even simple trained algorithms).

learning: The AI would have to understand that other agents are responding to its behavior, realize that those agents would eventually cooperate with a gullible agent, and suffer losses while waiting for that to occur. A “neutral” algorithm capable of doing this would create the Digital Eye scenario and is, luckily, not yet a reality.<sup>328</sup> However, it is unclear when pricing algorithms may reach such sophistication, and how antitrust law might handle the Digital Eye remains an open problem.

### Conclusion

The spread of pricing algorithms has been met with a surge of scrutiny in scholarship and antitrust enforcement. Scholars have focused on scenarios with equally competent rival algorithms and warned that more sophisticated programs will stretch antitrust law’s ability to promote competition.<sup>329</sup> In *FTC v. Amazon.com, Inc.*, the Commission levied Section 5 against Amazon for using a price-raising tool that “induced” and “manipulated” the other programs.<sup>330</sup>

Unsophisticated algorithms, however, carry substantial risks of their own. Empirical studies and guides on pricing tools suggest that simple programs that mimic competing prices are prevalent.<sup>331</sup> These “gullible programs” are definitionally interdependent and can unintentionally cause anticompetitive effects.<sup>332</sup> Without human agreement, intent, or knowledge, their behavior is beyond the reach of even expanded conceptions of antitrust law.<sup>333</sup> To condemn them under antitrust law would contradict both precedent and established policy choices that maintain clear divisions between competitive and anticompetitive behavior.<sup>334</sup>

This Note contributes this “Gullible Agent” scenario to Ezrachi and Stucke’s categorization. Further, this Note argues that to broadly prevent algorithms from being induced and manipulated, those algorithms’ users should be held to a standard of care. While focusing on the unsophisticated firm in an anticompetitive dynamic is unusual, establishing a minimum standard for pricing algorithms disincentivizes the actors that effectively

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328. See Gautier et al., *supra* note 20, at 415-20 (discussing hurdles to the deployment of autonomously colluding pricing algorithms).

329. Ezrachi & Stucke, *supra* note 13, at 1784 tbl.1 (showing increasingly tenuous liability as algorithm complexity rises).

330. Complaint [Public Redacted Version], *supra* note 4, at 119.

331. See sources cited *supra* notes 224-25.

332. *Supra* Part III.A.

333. *Supra* Part III.C.

334. See *supra* note 237 and accompanying text; *supra* notes 245-50 and accompanying text.

punish deviation from high prices.<sup>335</sup> It also prevents blind interdependence without raising challenging technical problems or discouraging procompetitive sophistication.<sup>336</sup>

Such a policy carries risks: Encouraging shared upstream algorithms may increase the likelihood of collusion between sophisticated programs.<sup>337</sup> But even a small increase in sophistication makes collaboration much more challenging,<sup>338</sup> whereas a still-unrealized level of sophistication is required for collaboration to become likely again.<sup>339</sup>

The ultimate question raised by the Digital Eye’s sophisticated collaborators remains unanswered. These hypothetical pricing algorithms, by virtue of their sophistication, can cooperate without human knowledge or intent. Their behavior is beyond current antitrust law, and their complexity makes investigations or guardrails challenging. Further work is needed to understand whether such programs are coming and how they might be addressed. At present, however, gullible agents should be scrutinized so their current anticompetitive risks do not go unaddressed.

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335. *See supra* notes 246-47 and accompanying text.

336. *See supra* notes 238-44 and accompanying text; *see also supra* notes 30-31 and accompanying text (discussing the benefits of pricing algorithms).

337. *Supra* notes 311-15 and accompanying text.

338. *See Wang et al., supra* note 25, at 4-5.

339. *See supra* note 274.