

PREDATORY PRICING ALGORITHMS

CHRISTOPHER R. LESLIE*

In the battle for market supremacy, many firms are employing pricing software that removes humans from price-setting decisions. These pricing algorithms fundamentally change the dynamics of competition and have important implications for anti-trust law. The Sherman Act has two operative provisions. Section One condemns agreements between firms that unreasonably restrain trade, such as price-fixing agreements. Section Two prohibits monopolizing a relevant market through anticompetitive conduct. Although a considerable body of excellent scholarship explains how pricing algorithms can collude to fix prices in violation of Section One, no scholarship discusses how algorithmic pricing could violate Section Two.

This Article addresses how pricing algorithms can facilitate illegal monopolization through predatory pricing. Predatory pricing is a two-stage strategy. First, in the predation phase, the predator charges a price below its costs, reckoning that its rivals will exit the market because they cannot make profitable sales at that price. The predator willingly incurs losses in order to force its rivals from the market. Second, during the recoupment phase, after its rivals have exited the market, the predator recovers its earlier losses by charging a monopoly price.

Theorists have asserted that predatory pricing claims are inherently implausible for three reasons: (1) The predator must suffer disproportionately outsized losses because it controls a larger share of the market; (2) predatory pricing threats are not credible because a firm cannot believably commit to below-cost pricing; and (3) firms that exited the market during the predation phase will simply reenter the market during the recoupment phase. Based on these theoretical arguments, federal judges consistently reject predatory pricing claims.

This Article explains how algorithmic pricing undermines all three theoretical arguments claiming that predatory pricing is not a credible route to monopoly. First, a predatory firm can use pricing algorithms to identify and target its rivals' customers for below-cost pricing, while continuing to charge their own existing customers a profitable price, which minimizes the predator's losses during the predation phase. Second, algorithms can commit to price predation in ways humans cannot. Third, pricing algorithms present several new avenues for recouping the losses associated with predatory pricing, including algorithmic lock-in and price manipulation. In short, even if one believed that predatory pricing was implausible in the past, the proliferation of algorithmic pricing changes everything. Because pricing algorithms invalidate the theories behind the current judicial skepticism, this evolving technology requires federal courts to revisit the letter and spirit of antitrust law's treatment of predatory pricing claims.

* Copyright © 2023 by Christopher R. Leslie, Chancellor's Professor of Law, University of California, Irvine School of Law. The author thanks Dan Burk, Thomas Cheng, Lee Fennell, Mark Lemley, Julian Nowag, Tony Reese, and Sam Weinstein for comments on earlier drafts.

INTRODUCTION	50
I. PREDATORY PRICING: LAW AND THEORY	55
A. <i>Predatory Pricing as Monopoly Conduct</i>	55
B. <i>The Myth of Implausibility</i>	58
II. REAL PREDATION THROUGH ARTIFICIAL INTELLIGENCE	63
A. <i>The Rise of Algorithmic Pricing</i>	64
B. <i>Algorithmic Solutions to Predators' Predicaments</i> ...	67
1. <i>Targeted Predation</i>	67
a. Identifying the Targets	70
b. Algorithmic Price Discrimination	72
2. <i>Algorithmic Commitment</i>	80
3. <i>Recoupment by Algorithm</i>	84
a. Big Data as a Barrier to Entry	87
b. Recoupment Through Automated Restocking	90
c. The Time Needed to Recoup	91
d. Network Effects	92
e. Customer Loyalty	94
C. <i>The Battle of the Algorithms</i>	96
D. <i>Summary</i>	100
III. THE DOCTRINAL AND POLICY IMPLICATIONS OF ALGORITHMIC PREDATION	100
A. <i>The Significance of Individual Transactions</i>	101
B. <i>Discovery in the Algorithmic Age</i>	105
C. <i>The Irrelevance of Recoupment</i>	107
CONCLUSION	110

INTRODUCTION

During the height of the Cold War, the American and Soviet militaries maintained arsenals of nuclear weapons aimed at each other's populations, military targets, and economic assets. American leaders debated various strategies to maximize nuclear deterrence. Anxious that Soviet missiles could immobilize America's nuclear arsenal preemptively, some tacticians advocated a launch-on-warning (LOW) strategy, whereby sensors would monitor for Soviet military activity and American leaders would launch U.S. nuclear weapons based on computer detection of an enemy missile attack.¹ False alarms from

¹ BRUCE G. BLAIR, *THE LOGIC OF ACCIDENTAL NUCLEAR WAR* 168 (1993) ("Launch on warning meant that tactical warning systems played a critical role: early warning sensors designed to observe the launching and transit of strategic delivery vehicles provided tactical information that would have been the triggering condition for disseminating launch orders."); RICHARD SMOKE, *NATIONAL SECURITY AND THE NUCLEAR DILEMMA* 229

sensors, however, were common, and LOW created a significant risk of accidental nuclear war.² Reliance on computers in this context came with too many risks.³

Although the American military never fully implemented LOW,⁴ decades later, many American businesses did so, albeit with far less lethal weapons. Machines and artificial intelligence (AI) serve as tacticians and soldiers in a new type of conflict: price wars. In the battle for market supremacy, many dominant firms employ pricing software that automatically responds to a rival's price reduction by slashing their own prices to undercut their competitors. These pricing algorithms remove humans from the decisionmaking process and shift the war rooms of capitalism to cyberspace. The wealthiest firms can purchase the most powerful—most trigger-happy—algorithms that can reduce prices faster than it takes to read this sentence.⁵ Pricing technologies can help a dominant firm obliterate its rivals.

While technology has evolved in sophistication and speed, one fact remains constant: From Cold Wars to price wars, automation fundamentally changes the dynamics of competition. This insight has important implications for antitrust law. The Sherman Act has two operative provisions. Section One condemns agreements between firms that unreasonably restrain trade, such as price-fixing conspiracies.⁶ Antitrust professors and practitioners have developed a considerable body of scholarship on the threat of pricing algorithms

(1984) (“Launch on warning means that a nation plans to launch its counterstrike when its radars and computers indicate that an enemy attack is on its way. In a sense this is the ultimate answer to fears that one’s own missiles or control centers may be vulnerable.”).

² SMOKE, *supra* note 1, at 229 (“False alarms are so prevalent that many analysts fear a launch on warning policy adopted by either superpower would make a wholesale nuclear war likely within the foreseeable future.”); BLAIR, *supra* note 1, at 168 (“This reliance on sensors to make decisions during the short flight times of ballistic missiles—fifteen to thirty minutes—increased the danger of inadvertent war.”).

³ See JOSEPH S. NYE, JR., NUCLEAR ETHICS 118 (1986) (“[A] policy of launching our missiles on warning would help to deter a Soviet first strike . . . but at the cost of greatly increased vulnerability to catastrophic failure . . .”).

⁴ SMOKE, *supra* note 1, at 229 (“The United States has never had a launch on warning policy, and the overwhelming majority of national security specialists have always opposed it.”); BLAIR, *supra* note 1, at 169 (“Rapid reaction or launch on warning is controversial. U.S. officials acknowledged that this option existed as a capability, but they never conceded and often strenuously denied that it had become the cornerstone of U.S. operational plans.”).

⁵ See ARIEL EZRACHI & MAURICE E. STUCKE, VIRTUAL COMPETITION: THE PROMISE AND PERILS OF THE ALGORITHM-DRIVEN ECONOMY 62 (2016) (“So as competitors’ prices shift online, their algorithms can assess and adjust prices—even for particular individuals at particular times and for thousands of products—within milliseconds.”).

⁶ 15 U.S.C. § 1.

communicating and colluding with each other to fix prices in violation of Section One.⁷

In contrast, no attention has been paid to how algorithmic pricing could implicate Section Two of the Sherman Act,⁸ which prohibits a firm from monopolizing (or attempting to monopolize) a relevant market.⁹ Illegal monopolization occurs when a firm employs anticompetitive conduct to acquire or maintain monopoly power.¹⁰ The Sherman Act's text does not mention or proscribe any particular acts. Instead, Congress intended federal courts to develop a body of common law that defines what actions constitute monopoly conduct that violates the statute.¹¹

⁷ See, e.g., Michal S. Gal, *Algorithms as Illegal Agreements*, 34 BERKELEY TECH. L.J. 67, 91–92 (2019) (“[F]irms can in theory coordinate with respect to the prices charged to each and every consumer. While such coordination would be almost impossible for humans, it can be facilitated by algorithms under certain market conditions.”); Ariel Ezrachi & Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition*, 2017 U. ILL. L. REV. 1775, 1780 (2017) (“Online trade platforms enable sellers to segment the market by using dynamic pricing.”); Salil K. Mehra, *Antitrust and the Robo-Seller: Competition in the Time of Algorithms*, 100 MINN. L. REV. 1323, 1356 (2016) (noting that traditional deterrent mechanisms against Section One price fixing is “likely to prove less effective in a world of robo-sellers”); Brendan Ballou, *The “No Collusion” Rule*, 32 STAN. L. & POL’Y REV. 213, 222 (2021) (“Companies occasionally use pricing algorithms to coordinate with one another, essentially automating collusive decisions that might otherwise be made by people.”); Terrell McSweeney & Brian O’Dea, *The Implications of Algorithmic Pricing for Coordinated Effects Analysis and Price Discrimination Markets in Antitrust Enforcement*, ANTITRUST, Fall 2017, at 75, 75 (“[T]he Department of Justice recently prosecuted two e-commerce sellers for agreeing to align their pricing algorithms to increase online prices for posters.”). Antitrust plaintiffs have sued Uber drivers for illegally fixing prices by agreeing to charge the prices dictated by Uber’s pricing algorithm. See *Meyer v. Kalanick*, 174 F. Supp. 3d 817, 823 (S.D.N.Y. 2016) (“The capacity to generate ‘supra-competitive prices’ through agreement to the Uber pricing algorithm thus provides, according to plaintiff, a ‘common motive to conspire’ on the part of Uber drivers.”); *Meyer v. Kalanick*, 291 F. Supp. 3d 526, 530 (S.D.N.Y. 2018) (“Meyer’s basic claim is that Kalanick arranged for Uber drivers to use Uber’s pricing algorithm to determine the amounts to charge to Uber riders, thereby restricting competition among drivers who would otherwise compete on price to the benefit of riders such as Meyer.”).

⁸ 15 U.S.C. § 2.

⁹ Section Two also condemns conspiracies to monopolize. *Id.*

¹⁰ *United States v. Grinnell Corp.*, 384 U.S. 563, 570–71 (1966) (establishing the elements of illegal monopolization: “(1) the possession of monopoly power in the relevant market and (2) the willful acquisition or maintenance of that power as distinguished from growth or development as a consequence of a superior product, business acumen, or historic accident”). A firm engages in illegal attempted monopolization when it engages in anticompetitive conduct while possessing dominant market share and a specific intent to monopolize the market. *Spectrum Sports, Inc. v. McQuillan*, 506 U.S. 447, 456 (1993) (establishing the elements of illegal attempted monopolization: “(1) . . . the defendant has engaged in predatory or anticompetitive conduct with (2) a specific intent to monopolize and (3) a dangerous probability of achieving monopoly power”).

¹¹ See *Leegin Creative Leather Prods., Inc. v. PSKS, Inc.*, 551 U.S. 877, 899 (2007) (“From the beginning the Court has treated the Sherman Act as a common-law statute.”);

Over a century ago, the Supreme Court condemned predatory pricing as a form of illegal monopoly conduct.¹² Predatory pricing is a two-stage strategy. First, in the predation phase, the predator charges a price below its costs, reckoning that its rivals will exit the market because they cannot make profitable sales at that price. The predator willingly incurs losses as the price for forcing its rivals from the market. Second, during the recoupment phase, after its rivals have exited the market, the monopolist seeks to recover its earlier losses by charging a supracompetitive price. Although some consumers pay artificially low prices during the predation phase, all consumers suffer antitrust injury when forced to pay a monopoly price during the recoupment phase. To prove a predatory pricing claim, an antitrust plaintiff must show that the defendant-monopolist priced “below an appropriate measure of its . . . costs” and the defendant had a dangerous probability of recouping its losses.¹³ These two elements correspond, respectively, to the predation phase and recoupment phase.

Many federal opinions assert that predatory pricing claims are inherently implausible because the strategy has a high cost and low probability of success.¹⁴ This skepticism is largely based on simplistic—and unproven—theories and misrepresentations of the facts of important historical cases.¹⁵ Nevertheless, based on their incorrect assumption that predatory pricing is implausible, some courts have made predatory pricing claims virtually impossible to prove.

Yet even if one believed that predatory pricing was implausible in the past, the proliferation of algorithmic pricing changes everything. This Article explains how algorithmic pricing undermines all three major theoretical arguments that predatory pricing is not a credible route to monopoly. Part One briefly reviews the legal history of predatory pricing law and then presents the three principal arguments used to assert that predatory pricing claims are inherently implausible. First, some economists argue that the predator must suffer disproportionately outsized losses because it controls a larger share of the market. Second, some commentators assert that predatory pricing threats are not credible because a firm cannot believably commit to

State Oil Co. v. Khan, 522 U.S. 3, 20–21 (1997) (“Congress ‘expected the courts to give shape to the statute’s broad mandate by drawing on common-law tradition.’” (quoting Nat’l Soc’y of Pro. Eng’rs v. United States, 435 U.S. 679, 688 (1978))).

¹² Standard Oil Co. v. United States, 221 U.S. 1 (1911).

¹³ Brooke Grp. Ltd. v. Brown & Williamson Tobacco Corp., 509 U.S. 209, 222, 224 (1993).

¹⁴ See, e.g., Bathke v. Casey’s Gen. Stores, Inc., 64 F.3d 340, 343 (8th Cir. 1995) (citing Supreme Court cases commenting on the alleged rarity of successful predatory pricing schemes and the high costs of an erroneous finding of liability).

¹⁵ See *infra* notes 57–70 and accompanying text.

below-cost pricing. Third, theorists predict that firms that exited the market during the predation phase will simply reenter the market during the recoupment phase, preventing the predator from recouping the losses it incurred during the predation phase. Seeing these risks, the argument goes, no rational firm would ever attempt to monopolize a market through predatory pricing.

Part Two explains why these theoretical arguments should hold no sway. They were never correct, having been disproven before they were even made, because historical monopolists, such as the Standard Oil Company (“Standard” or “Standard Oil”), had found ways to solve these problems. More importantly, pricing algorithms render these pre-AI arguments largely obsolete in the current era. First, predatory firms can use AI to identify and target their rivals’ customers for below-cost pricing while continuing to charge higher prices to their existing customers. Such algorithmic price discrimination in the service of predatory pricing significantly minimizes the predator’s losses during the predation phase. Second, pricing algorithms can demonstrate a more credible commitment to predation. Pricing algorithms present a new mechanism for would-be monopolists to communicate their threats of predation in a credible fashion. Third, pricing algorithms present several new avenues for recouping the losses associated with predatory pricing. For example, through strategic use of pricing algorithms, a monopolist can manipulate what prices consumers see in ways that generate consumer loyalty and lock-in in ways that block rivals from being able to reenter the market profitably. Pricing algorithms also accelerate recoupment through algorithmic restocking and network effects.

Part Three argues that the evolution of algorithmic pricing should inform how antitrust doctrine treats predatory pricing claims. For example, when determining whether a defendant has priced below its cost, courts should look at individual sales—i.e., those customers targeted by the algorithm for below-cost prices—not overall profitability. Examining price in this fashion should affect discovery. In particular, courts should allow appropriate discovery of pricing data, including pricing algorithms themselves. Furthermore, the prospect of algorithmic predatory pricing requires courts to reconsider the recoupment requirement for predatory pricing claims, an element that is ever more likely to protect illegal monopolists from accountability.

I

PREDATORY PRICING: LAW AND THEORY

Section Two of the Sherman Act condemns both monopolization and attempted monopolization.¹⁶ Being a monopolist is not illegal,¹⁷ but acquiring or maintaining monopoly power through monopoly conduct does violate Section Two.¹⁸ Through common-law development, federal courts have recognized myriad acts that constitute monopoly conduct.¹⁹ Courts often define “monopoly conduct” in contrast to “competition on the merits,” which represents any legal means of acquiring monopoly power, such as by being more efficient than one’s rivals.²⁰

This Part explains how courts came to condemn predatory pricing as monopoly conduct, how predatory pricing injures competition and hurts consumers, and how unsubstantiated economic theory has undermined antitrust doctrine against predatory pricing.

A. Predatory Pricing as Monopoly Conduct

The Supreme Court first condemned predatory pricing as anticompetitive conduct in 1911, when it decided *Standard Oil Co. v. United States*.²¹ Prior to the government’s prosecution of Standard Oil, investigative journalist Ida Tarbell spent years reading the reports of state investigations and Standard Oil’s internal records and proved that the oil behemoth had monopolized the market through price pre-

¹⁶ 15 U.S.C. § 2.

¹⁷ *Abraham & Veneklasen Joint Venture v. Am. Quarter Horse Ass’n*, 776 F.3d 321, 334 (5th Cir. 2015) (“Having or acquiring a monopoly is not in and of itself illegal.”).

¹⁸ *United States v. Grinnell Corp.*, 384 U.S. 563, 570–71 (1966) (“[M]onopoly under § 2 of the Sherman Act has two elements: (1) the possession of monopoly power in the relevant market and (2) the willful acquisition or maintenance of that power as distinguished from growth or development as a consequence of a superior product, business acumen, or historic accident.”). In order to prevail on a predatory pricing claim under Section Two of the Sherman Act, the plaintiff must first prove that the defendant possessed monopoly power in a relevant product—or had a dangerous probability of doing so if the plaintiff is bringing an attempted monopolization claim. This Article takes the first element—monopoly power—as given and focuses on those components that are unique to a predatory pricing claim: below-cost pricing and a dangerous probability of recouping those losses.

¹⁹ See Christopher R. Leslie, *Monopolization Through Patent Theft*, 103 GEO. L.J. 47, 53 (2014) (“When opinions hold that a particular fact pattern constitutes monopoly conduct, subsequent courts analogize or distinguish these earlier fact patterns. Through this common law approach, antitrust courts decide what conduct by a monopolist constitutes monopoly conduct sufficient to satisfy the second element of Grinnell.”).

²⁰ See *Aspen Skiing Co. v. Aspen Highlands Skiing Corp.*, 472 U.S. 585, 605 n.32 (1985) (quoting PHILLIP AREEDA & DONALD F. TURNER, *ANTITRUST LAW* 78 (1978)).

²¹ *Standard Oil Co. v. United States*, 221 U.S. 1 (1911); see also Christopher R. Leslie, *Revisiting the Revisionist History of Standard Oil*, 85 S. CAL. L. REV. 573 (2012) (discussing the history of the *Standard Oil* case).

dition.²² Building on the work of Tarbell, the Bureau of Corporations,²³ and others, the U.S. Attorney General prosecuted Standard Oil for violating the Sherman Act through numerous forms of anticompetitive conduct, including below-cost pricing in over one hundred local markets.²⁴ The Supreme Court found Standard Oil liable and ordered that the firm be dissolved into several smaller regional units.²⁵ Along with *United States v. American Tobacco Co.*,²⁶ decided the same year, the *Standard Oil* opinion created the federal precedent holding that predatory pricing violates antitrust law.²⁷

Predatory pricing contravenes Section Two of the Sherman Act because when a dominant firm uses below-cost pricing to monopolize—or attempt to monopolize—a relevant market, such conduct is not efficiency-enhancing competition on the merits.²⁸ Predatory pricing is not efficient; indeed, both stages of a predatory pricing scheme inflict inefficiency. Below-cost pricing during the predation phase induces consumers to purchase inefficiently excessive amounts of the product, which results in inputs being shifted away from more beneficial uses.²⁹ This overconsumption is a form of deadweight loss.³⁰

²² 2 IDA M. TARBELL, *THE HISTORY OF THE STANDARD OIL COMPANY* 42–62, 221 (1904) (detailing the price predation and price cutting tactics Standard Oil engaged in to eliminate competition across the country); Leslie, *supra* note 21, at 574 (“Tarbell showed that Standard did not merely charge the competitive price in [competitive markets]. Rather, it charged a price below cost in order to drive competitors from the market.”).

²³ U.S. BUREAU OF CORP., *REPORT OF THE COMMISSIONER OF CORPORATIONS ON THE PETROLEUM INDUSTRY, PT. II, PRICES & PROFITS* 438 (1907) (“When necessary, [Standard Oil] puts the prices in a given locality down even below its own cost of manufacture, transportation, and delivery. Instances have been known where the Standard has virtually given oil away to destroy the business of independent concerns.”).

²⁴ See Reply Brief for the United States at 44, *Standard Oil Co. v. United States*, 221 U.S. 1 (1911) (No. 398), 1911 WL 19167.

²⁵ *Standard Oil Co. v. United States*, 221 U.S. 1, 78 (1911) (affirming district court’s dissolution order with minor modifications).

²⁶ *United States v. American Tobacco Co.*, 221 U.S. 106 (1911).

²⁷ See *United States v. A. Schrader’s Son*, 264 F. 175, 181 (N.D. Ohio 1919) (noting that both the *Standard Oil* and *American Tobacco* decisions were grounded in price cutting as a way of establishing monopoly and violating Section Two of the Sherman Act), *rev’d*, 252 U.S. 85 (1920); see also *Malcolm v. Marathon Oil Co.*, 642 F.2d 845, 853 n.16 (5th Cir. 1981) (“Predatory pricing violates § 2 of the Sherman Act, 15 U.S.C. § 2, when there is an attempt to monopolize” (citing *Standard Oil Co. v. United States*, 221 U.S. 1, 43 (1911))).

²⁸ Cf. *Weyerhaeuser Co. v. Ross-Simmons Hardwood Lumber Co.*, 549 U.S. 312, 319 (2007) (“The first prong of the test—requiring that prices be below cost—is necessary because [a]s a general rule, the exclusionary effect of prices above a relevant measure of cost either reflects the lower cost structure of the alleged predator, and so represents competition on the merits” (quoting *Brooke Grp. Ltd. v. Brown & Williamson Tobacco Corp.*, 509 U.S. 209, 223 (1993))).

²⁹ See Christopher R. Leslie, *Hindsight Bias in Antitrust Law*, 71 VAND. L. REV. 1527, 1578 (2018) (“These market disruptions shift resources away from their most efficient uses.”); Paul L. Joskow & Alvin K. Klevorick, *A Framework for Analyzing Predatory*

The Supreme Court in *Brooke Group Ltd. v. Brown & Williamson Tobacco Corp.* recognized that “unsuccessful predatory pricing may encourage some inefficient substitution toward the product being sold at less than its cost”³¹ These inaccurate market signals can distort consumers’ purchasing plans in ways that create long-term inefficiencies.³² In addition to allocative inefficiency, below-cost pricing wastes societal resources by “impos[ing] enormous losses on rivals who must spend resources defending themselves or make costly exits from the market in favor of other firms.”³³ Consequently, the predation phase creates inefficiency for both consumers and producers.

During the recoupment phase, the predatory firm’s monopoly pricing creates inefficiency by reducing output and consumption below optimal levels. In theory, other firms could enter the market, expand output, and bid the price down.³⁴ But, in reality, efficient rivals are excluded from the market if the predatory firm uses the threat of future below-cost pricing as a barrier to entry.³⁵ In addition to the harms suffered by excluded rivals, all consumers are injured by the monopoly price, especially those who did not purchase during the predation phase and, therefore, never benefited from the earlier lower price.³⁶ The inefficiencies and harms imposed by monopolization through below-cost pricing render the strategy illegal under antitrust

Pricing Policy, 89 YALE L.J. 213, 224 n.31 (1979) (“If price is less than short-run marginal cost, and if demand is at all elastic, . . . consumers will purchase too much . . . [and] too many resources will be devoted to producing the particular good in the short run.”).

³⁰ See Daniel A. Crane, *The Paradox of Predatory Pricing*, 91 CORNELL L. REV. 1, 35 (2005) (“[N]onpredatory below-cost pricing is allocatively inefficient, even if it does not lead to, or threaten, later supracompetitive pricing, because it induces the consumption of goods by some consumers who value them at less than the cost of production, creating a deadweight loss.”); F.M. Scherer, *Predatory Pricing and the Sherman Act: A Comment*, 89 HARV. L. REV. 869, 872–73 (1976) (discussing deadweight loss and concluding “short-run allocative inefficiencies associated with pricing below marginal cost can hardly be ignored”); see also Christopher R. Leslie, *Antitrust Damages and Deadweight Loss*, 51 ANTITRUST BULL. 521, 524–26 (2006) (discussing concept of deadweight loss in antitrust law).

³¹ *Brooke Group*, 509 U.S. at 224.

³² See Christopher R. Leslie, *Predatory Pricing and Recoupment*, 113 COLUM. L. REV. 1695, 1743 (2013) (“Professor [Oliver] Williamson has explained that if consumers adapt their consumption and investment patterns on the mistaken belief that the (predatory) low price is enduring, consumers can suffer net losses if they incur fixed costs based on their assumption that the relative prices were stable.”); see also Crane, *supra* note 30, at 35 (“[B]elow-cost, nonexclusionary prices may harm consumers by sending false price signals that result in poor consumption planning by consumers.”).

³³ Herbert Hovenkamp, *Antitrust’s Protected Classes*, 88 MICH. L. REV. 1, 36 (1989).

³⁴ See *infra* notes 52–56 and accompanying text.

³⁵ See *infra* note 216 and accompanying text.

³⁶ See Leslie, *supra* note 32, at 1742 (“Consumers paying monopoly prices in the post-predation period are injured even if the monopoly price is insufficient to recoup the investment in predatory pricing.”).

laws. For decades, predatory pricing was a well-recognized antitrust claim, which plaintiffs often succeeded in proving.³⁷

B. *The Myth of Implausibility*

The success of predatory pricing claims ground to a screeching halt with the ascent of the Chicago School of Law and Economics, which asserted that firms do not price below cost. The Chicago School's doubts about predatory pricing claims influenced the Supreme Court's opinion in *Matsushita Electrical Industrial Co. v. Zenith Radio Corp.*,³⁸ which cited Chicago School scholarship to claim the existence of "a consensus among commentators that predatory pricing schemes are rarely tried, and even more rarely successful."³⁹ No such consensus existed.⁴⁰ But based on the assertion that firms do not engage in predatory pricing, the Supreme Court set out to make predatory pricing claims hard to prove. Most notably, in *Brooke Group Ltd. v. Brown & Williamson Tobacco Corp.*,⁴¹ the Supreme Court required that predatory pricing plaintiffs prove that the defendant enjoyed a "dangerous probability" of recouping the losses it incurred during the predation phase.⁴² As applied by federal courts, this recoupment requirement is virtually impossible to prove.⁴³

Theorists argue that no rational firm would engage in predatory pricing for three reasons. First, they assume that price predation is irrational because the predator would necessarily suffer losses several-fold greater than its quarry. For example, in his work claiming that Standard Oil never engaged in predatory pricing, influential Chicago School economist John McGee (whose work was cited by the *Matsushita* Court) argued that, because it controlled 75% of the market, Standard Oil would have to incur three times more losses

³⁷ See Patrick Bolton, Joseph F. Brodley & Michael H. Riordan, *Predatory Pricing: Strategic Theory and Legal Policy*, 88 GEO. L.J. 2239, 2250 (2000) ("Plaintiffs won most litigated [predatory pricing] cases, including those they probably should have lost."); James D. Hurwitz & William E. Kovacic, *Judicial Analysis of Predation: The Emerging Trends*, 35 VAND. L. REV. 63, 141 (1982) (noting a study that found that "in cases decided prior to 1971 the plaintiff was 'legally adjudged' to have suffered from predatory pricing behavior in ninety-five cases, whereas the defendants had won only twenty-eight").

³⁸ 475 U.S. 574 (1986).

³⁹ *Id.* at 589 (citations omitted).

⁴⁰ See Christopher R. Leslie, *Rationality Analysis in Antitrust*, 158 U. PA. L. REV. 261, 289 (2010) (collecting authorities contrary to the alleged consensus).

⁴¹ 509 U.S. 209 (1993).

⁴² *Id.* at 224 ("Recoupment is the ultimate object of an unlawful predatory pricing scheme; it is the means by which a predator profits from predation.").

⁴³ See Sandeep Vaheesan, *Reconsidering Brooke Group: Predatory Pricing in Light of the Empirical Learning*, 12 BERKELEY BUS. L.J. 81, 82 (2015) ("The *Brooke Group* test has made it virtually impossible for plaintiffs with even meritorious predatory pricing claims to go to trial.").

than all its rivals combined.⁴⁴ Adopting McGee's assumption of asymmetric losses but ramping up the numbers, Professor David Friedman asserted: "If I am selling 90 percent of all petroleum, a particular competitor is selling 1 percent, and we both sell at the same price and have the same average cost, I lose \$90 for every \$1 he loses."⁴⁵ Robert Bork, whose work the *Matsushita* Court also cited, asserted that "price cutting, though conventionally viewed with grave suspicion, does not provide a likely means of predation because it requires the predator to bear losses that are much larger, both absolutely and proportionally, than those inflicted on the intended victim."⁴⁶ Under this thinking, "as the predator succeeds in acquiring more market share, its relative losses increase as well."⁴⁷ These scholars notably assume that the dominant firm must cut price across all units of its product, driving up losses and making recoupment all but inconceivable.⁴⁸

Second, theorists argue that threats to price below cost until rivals exit the market are not credible. For a predatory pricing scheme to succeed, the predator must convince its rivals that it is committed to incurring losses until the rivals leave the market.⁴⁹ Sometimes coupled with the assumption of asymmetric losses, Chicago theory argues that such commitments are not credible because no rational firm would pledge to make unprofitable sales for the foreseeable future when the strategy is unlikely to pay off in the long run. Theorists have predicted that firms will not follow through with predatory threats because rational firms will conclude that sharing the market makes more sense than predation.⁵⁰ Other theorists propose that commitments to below-cost pricing are not credible because impatient shareholders will not

⁴⁴ John S. McGee, *Predatory Price Cutting: The Standard Oil (N.J.) Case*, 1 J.L. & ECON. 137, 140 (1958) ("Standard's market share was often 75 per cent or more. In the 75 percent case the monopolizer would sell three times as much as all competitors taken together, and, on the assumption of equal unit costs, would lose roughly three times as much as all of them taken together.").

⁴⁵ DAVID D. FRIEDMAN, *LAW'S ORDER: WHAT ECONOMICS HAS TO DO WITH LAW AND WHY IT MATTERS* 249 (2000).

⁴⁶ ROBERT H. BORK, *THE ANTITRUST PARADOX* 148 (1978).

⁴⁷ Leslie, *supra* note 32, at 1732 (first citing BORK, *supra* note 46, at 149; and then citing John S. McGee, *Predatory Pricing Revisited*, 23 J.L. & ECON. 289, 296 (1980)).

⁴⁸ See Leslie, *supra* note 21, at 592 ("The revisionist history assumes that the predator reduces the price below cost for all of its sales." (citing BORK, *supra* note 46, at 151)).

⁴⁹ See Daniel A. Crane, *Antitrust Modesty*, 105 MICH. L. REV. 1193, 1204 (2007) ("[S]ome strategic anticompetitive behavior, like predatory pricing, is only likely to work if a dominant firm succeeds in signaling its predatory commitment to rivals.").

⁵⁰ See, e.g., M. Steven Wagle, *Predatory Pricing, A Case Study: Matsushita Electric Industries Co. v. Zenith Radio Corporation*, 22 CREIGHTON L. REV. 89, 129 (1988) ("[T]he predator's losses . . . will exceed [a competitor's] own [losses] as long as its market share is smaller and it is equally efficient . . . [A] rational incumbent will conclude that a duopoly . . . is more desirable than following a predatory strategy.").

tolerate losses and will remove any executives and managers that pursue predatory pricing strategies.⁵¹ Assuming that predatory commitments are not credible, some theorists argue that predatory pricing is not possible.

Third, theorists argue that predatory pricing is not a plausible strategy because rivals will simply exit the market temporarily and then reenter once the monopolist raises prices during the recoupment phase.⁵² McGee argued that if a dominant firm engages in below-cost pricing, its rivals will suspend operations, but their “physical capacity remains, and will be brought back into play by some opportunist once the monopolizer raises prices to enjoy the fruits of the battle he has spent so much in winning.”⁵³ He assumed that rivals will simply leave their factories and offices empty and idle and that they can restart their operations with the flick of a switch. Robert Bork embellished this claim even further, asserting (without any evidence) that “ease of entry will be symmetrical with ease of exit”⁵⁴ Bork assumed that the process of making and selling products is just as easy as not doing so—a proposition that no successful businessperson has endorsed. Both commentators argued that vanquished rivals will merely sit on the sidelines—paying their fixed costs and waiting for the price to rise—and then reenter the market.⁵⁵ Ultimately, because they assume reentry is inevitable, these theorists assert that the improbability of recoupment makes predatory pricing irrational.⁵⁶

⁵¹ See, e.g., David E.M. Sappington & J. Gregory Sidak, *Are Public Enterprises the Only Credible Predators?*, 67 U. CHI. L. REV. 271, 276 (2000) (“[A] firm’s predatory commitments will be credible only if its managers . . . cannot easily be removed by shareholders during the predatory period.”).

⁵² See McGee, *supra* note 44, at 140 (arguing that Standard Oil could not have monopolized the market through predatory pricing because “at some stage of the game the competitors may simply shut down operations temporarily, letting the monopolist take all the business (and all the losses), then simply resume operations when he raises prices again”); see also McGee, *supra* note 47, at 297 (suggesting that it is unlikely that competing firms shut down for long enough that their organization and variable resources are scattered, as they are incentivized to wait until the predatory firm raises prices).

⁵³ McGee, *supra* note 44, at 140–41 (“If price does not cover average variable costs, the operation is suspended. This will often leave the plant wholly intact.”).

⁵⁴ BORK, *supra* note 46, at 149; see also *id.* at 153 (“The easier it is to drive a firm from the market, the easier it will be for that firm or another to reenter once the predator begins to collect . . . monopoly profits. . . . [T]he more difficult entry is, the more difficult and expensive it will be to drive a rival out.”).

⁵⁵ See *id.* at 151 (“The victim . . . may be able to close down operations for the time being, paying only . . . fixed obligations and letting the predator supply the entire demand”).

⁵⁶ Harry S. Gerla, *The Psychology of Predatory Pricing: Why Predatory Pricing Pays*, 39 Sw. L.J. 755, 755–56 (1985) (describing these theorists’ views and critiquing them using experimental psychology).

Based on these theoretical arguments, some economists have argued that predatory pricing does not occur. In his seminal work rewriting the history—and factual record—of the *Standard Oil* case, McGee asserted that Standard did not engage in below-cost pricing, nor would any rational firm.⁵⁷ Despite its inaccuracy,⁵⁸ McGee's unfounded theory found a receptive audience in federal judges eager to clear their dockets of complex antitrust litigation.⁵⁹ The Third Circuit in *Advo, Inc. v. Philadelphia Newspapers, Inc.*, for example, affirmed summary judgment for defendants accused of predatory pricing by noting that the *Matsushita* Court “has cited approvingly the empirical work of McGee and others.”⁶⁰ McGee's article provided the origin story for the myth that predatory pricing does not occur.⁶¹

The assumption that predatory pricing does not occur has shaped antitrust doctrine. Most notably, courts created the recoupment requirement based on the assumption that predatory pricing does not happen.⁶² These theoretical arguments have influenced federal judges to reject predatory pricing claims. If a court believes that recoupment

⁵⁷ McGee, *supra* note 44, at 157 (“I can not find a single instance in which Standard used predatory price cutting to force a rival refiner to sell out . . . or to drive a competitor out of business. I do not believe that Standard even tried to do it; if it tried, it did not work.”); *see also* Richard J. Pierce, Jr., *Is Post-Chicago Economics Ready for the Courtroom? A Response to Professor Brennan*, 69 GEO. WASH. L. REV. 1103, 1106 (2001) (incorrectly asserting that “Professor McGee demonstrated that predatory pricing can never be implemented profitably in a manner that harms consumers”). McGee was incorrect on this score. Leslie, *supra* note 21 at 579–99 (arguing that McGee was wrong to conclude that Standard did not engage in predatory pricing, which can be profitable).

⁵⁸ *See* James A. Dalton & Louis Esposito, *Predatory Price Cutting and Standard Oil: A Re-Examination of the Trial Record*, 22 RSCH. L. & ECON. 155, 158 (2007) (“[T]he [trial] Record [in *Standard Oil*] contains considerable evidence of predatory pricing. Simply stated, the Record does not support McGee's conclusion that Standard Oil did not engage in predatory pricing.”).

⁵⁹ *See, e.g.*, *Advo, Inc. v. Phila. Newspapers, Inc.*, 51 F.3d 1191, 1196 (3d Cir. 1995) (citing McGee, *supra* note 44, at 168–69) (“[A] seminal article demonstrated that John D. Rockefeller invariably used mergers, and not predatory pricing, to lessen competition in the oil industry.”).

⁶⁰ *Id.* at 1196 n.5 (citing *Matsushita Elec. Indus. Co. v. Zenith Radio Corp.*, 475 U.S. 574, 588–90 (1986)); *see also* Pierce, *supra* note 57, at 1117 (“McGee's analysis was instrumental in persuading the Supreme Court to issue two opinions in the past fifteen years in which it has expressed an extremely skeptical attitude toward predatory pricing complaints.”).

⁶¹ Leslie, *supra* note 21, at 588 (“Scholars invoke McGee for the propositions that predatory pricing is ‘seldom used,’ ‘extremely rare,’ and ‘does not exist.’”) (first quoting William H. Jordan, *Predatory Pricing After Brooke Group: The Problem of State “Sales Below Cost” Statutes*, 44 EMORY L.J. 267, 274 & n.25 (1995); then quoting Daniel R. Fischel, Andrew M. Rosenfield & Robert S. Stillman, *The Regulation of Banks and Bank Holding Companies*, 73 VA. L. REV. 301, 327 & n.79 (1987); and then citing Yeomin Yoon, *The Korean Chip Dumping Controversy: Are They Accused of Violating an Unjust Law?*, 19 N.C. J. INT'L L. & COM. REG. 247, 263–64, 264 n.101 (1994)).

⁶² Leslie, *supra* note 32, at 1759–60.

is unlikely, then it will prevent the predatory pricing claim from reaching a jury.⁶³ The recoupment requirement has made it exceedingly difficult for predatory pricing claims to survive summary judgment.⁶⁴ For example, accepting the asymmetric losses theory as true, some courts have rejected predatory pricing claims, reasoning that a monopolist “will suffer those losses over a much greater range of output, since it will be making the vast majority of sales in the market.”⁶⁵ Similarly, the Supreme Court in *Matsushita* asserted that “[t]he predators’ losses must actually *increase* as the conspiracy nears its objective: the greater the predators’ market share, the more products the predators sell; but since every sale brings with it a loss, an increase in market share also means an increase in predatory losses.”⁶⁶ This unproven hypothesis reinforced the majority’s assertion that predatory pricing is irrational.

Regarding the third assumption of easy reentry, courts routinely assume that alleged predatory pricing schemes would inevitably fail because firms would enter—or reenter—the market as soon as the predator raises prices.⁶⁷ By assuming that market entry is easy, courts declare that price predators are “doomed to failure.”⁶⁸ This triumph of naked theory is troubling because theorists provide no data to back up their factual claims.⁶⁹ But in their world, theory trumps reality.⁷⁰

As of late, the theorists have won the legal battle for the hearts, minds, and keyboards of federal judges.⁷¹ Theoretical arguments have

⁶³ See, e.g., *Stearns Airport Equip. Co. v. FMC Corp.*, 170 F.3d 518, 528 (5th Cir. 1999) (“If there is no likelihood of recoupment, it would seem improbable that a scheme would be launched. Given the high error cost of finding companies liable for cutting prices to the consumer, the court should thus refuse to infer predation.”).

⁶⁴ 3A PHILLIP E. AREEDA & HERBERT HOVENKAMP, *ANTITRUST LAW* § 726(d)(2), at 72 (3d ed. 2008) (“By the stringency of its demand for proof of recoupment, the Court cleared the way for summary rejection of most predatory pricing claims.”); Leslie, *supra* note 32, at 1740 (“By requiring plaintiffs to prove recoupment while instructing lower courts that recoupment does not happen, the Court invited lower courts to systematically reject predatory pricing claims.”).

⁶⁵ *Ne. Tel. Co. v. Am. Tel. & Tel. Co.*, 651 F.2d 76, 87 n.14, 96 (2d Cir. 1981) (citing *McGee*, *supra* note 47, at 295–97 (1980)) (reversing verdict for plaintiffs on predatory pricing).

⁶⁶ *Matsushita Elec. Indus. Co. v. Zenith Radio Corp.*, 475 U.S. 574, 593 n.17 (1986).

⁶⁷ See, e.g., *Stearns*, 170 F.3d at 530.

⁶⁸ *Advo, Inc. v. Phila. Newspapers, Inc.*, 51 F.3d 1191, 1200 (3d Cir. 1995).

⁶⁹ Leslie, *supra* note 21, at 599 (“McGee provided no empirical evidence to support his theoretical assertions.”).

⁷⁰ *Caller-Times Publ’g Co. v. Triad Commc’ns, Inc.*, 826 S.W.2d 576, 597 (Tex. 1992) (“That predatory conduct is of little concern represents one of the court’s major unstated premises. This belief rests not on economic proof but on a generalization that predatory pricing is rare which is derived largely from Bork in *Matsushita*.”).

⁷¹ *Sappington & Sidak*, *supra* note 51, at 275–76 (“The current body of predatory pricing jurisprudence, epitomized by the Supreme Court’s decisions in *Matsushita Electric*

driven predatory pricing opinions to be far more pro-defendant, and in today's courts, predatory pricing claims rarely succeed.⁷² This is troubling because these theories on the implausibility—and hence lack—of predatory pricing were always facile and incorrect. Part Two explains why and explores how advances in artificial intelligence and algorithmic pricing make these outdated theories even more inapplicable to the modern marketplace.

II

REAL PREDATION THROUGH ARTIFICIAL INTELLIGENCE

Price setting is inherent to capitalism. For millennia, farmers, shepherds, and merchants of all stripes personally set the prices at which they were willing to sell their wares and services. As barter systems were replaced by coins and currency, shrewd sellers sought to divine the maximum price that each buyer was willing to pay, while trying to balance short-term profits and long-term trading relationships.⁷³ Since the advent of the computer age, however, businesses began ceding pricing authority to machines. Artificial intelligence in the forms of pricing algorithms and software holds the promise of helping firms to set a more accurate profit-maximizing price.⁷⁴ But this promise is accompanied by peril.

Algorithmic pricing renders markets more susceptible to predatory pricing. This Part introduces pricing algorithms and explains how they can facilitate price predation. In particular, algorithmic pricing undermines the theoretical claims that price predation is inherently implausible.

Industries Co v Zenith Radio Corp and *Brooke*, embraces the skepticism of the Chicago School. Predatory pricing is, in the Court's view, rarely attempted and even more rarely successful." (citations omitted)).

⁷² See D. Daniel Sokol, *The Transformation of Vertical Restraints: Per Se Illegality, the Rule of Reason, and Per Se Legality*, 79 ANTITRUST L.J. 1003, 1014–15 (2014) (describing the effective disappearance of public enforcement actions in this area and the sharp decline in private plaintiffs' success rates).

⁷³ JOSEPH TUROW, *THE AISLES HAVE EYES: HOW RETAILERS TRACK YOUR SHOPPING, STRIP YOUR PRIVACY, AND DEFINE YOUR POWER* 27 (2017) ("As far back as biblical times buyers and sellers both inevitably took into account the characteristics and cues of the other as each side tried to gain the upper hand in the bargaining. The nature and the cost of the merchandise was therefore often tailored to the particular transaction."); *id.* at 28–29 (describing how peddlers developed and solidified customer relationships while ensuring sufficient current profits to pay existing obligations and survive).

⁷⁴ EZRACHI & STUCKE, *supra* note 5, at 100, 101–02 (2016).

A. *The Rise of Algorithmic Pricing*

Pricing algorithms are essentially computational codes, of different degrees of sophistication, that firms can use to set and adjust prices.⁷⁵ Because they vary wildly in complexity and function, the single label of “pricing algorithms” is an oversimplification that cannot accurately capture the multitude of code and software. In using the phrase “pricing algorithms,” we are talking about the capabilities—both actual and potential—across a broad category of AI.

Pricing algorithms allow for faster—and often more profitable—pricing decisions than humans could possibly make.⁷⁶ These decisions are based on data analytics involving massive amounts of historical and real-time market information,⁷⁷ including other sellers’ prices.⁷⁸ Large businesses are increasingly relying on algorithms to set prices.⁷⁹ Pricing algorithms are common in airline ticketing, hotel booking, insurance, entertainment, and much online retailing, where algorithms monitor rivals’ prices and change prices quickly and often.⁸⁰

⁷⁵ ORG. FOR ECON. COOP. & DEV., *ALGORITHMS AND COLLUSION: COMPETITION POLICY IN THE DIGITAL AGE* 16 (2017), <https://www.oecd.org/daf/competition/Algorithms-and-collusion-competition-policy-in-the-digital-age.pdf> [<https://perma.cc/3NR7-7A94>] [hereinafter OECD] (“Pricing algorithms are commonly understood as the computational codes run by sellers to automatically set prices to maximise profits, being particularly common in the airline, hotel booking, road transport, electricity and retail industries.”).

⁷⁶ *Id.*; Alexander MacKay & Samuel N. Weinstein, *Dynamic Pricing Algorithms, Consumer Harm, and Regulatory Response*, 100 WASH. U. L. REV. 111, 114 (2022) (“Algorithms can analyze much greater volumes of information in setting prices than can human agents And algorithms can react much more quickly to changing market conditions than can human agents, allowing sellers to set the most advantageous prices more of the time.”).

⁷⁷ Gal, *supra* note 7, at 78–79 (“In today’s world, characterized by big data, fast digital connectivity, and increased computational and storage capacity, algorithms may create significant advantages in decision-making. The most basic advantage they offer is speed in the collection, organization, and analysis of data, enabling exponentially quicker decisions and reactions.”).

⁷⁸ *Id.* at 80 (“Algorithms can also police other firms, by determining when another firm has strayed from the status quo and by setting trade conditions designed to deter firms from doing so.”).

⁷⁹ Inge Graef, *Algorithms and Fairness: What Role for Competition Law in Targeting Price Discrimination Towards End Consumers?*, 24 COLUM. J. EUR. L. 541, 541 (2018) (“Computers, rather than human actors, are increasingly setting prices.”); Ariel Ezrachi & Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition*, 2017 U. ILL. L. REV. 1775, 1780 (2017) (“Pricing algorithms dominate online sales of goods . . . and are widely used in hotel booking, and the travel, retail, sport, and entertainment industries.”); Mehra, *supra* note 7, at 1324 (“[Computers’] rising power, plus the growing ubiquity of the Internet, and increasingly sophisticated data-mining techniques have driven a rapid shift of pricing decisions away from human-decisionmakers in favor of algorithms”).

⁸⁰ Zach Y. Brown & Alexander MacKay, *Competition in Pricing Algorithms* 3 (Harv. Bus. Sch., Working Paper No. 20-067, 2021), https://www.hbs.edu/ris/Publication%20Files/20-067_71a112ae-f461-45da-8157-42763d61c015.pdf [<https://perma.cc/SSC2-7JP9>]

While basic algorithms can set prices in response to rules and parameters dictated by humans,⁸¹ more sophisticated algorithms—often called learning algorithms—can adapt on their own.⁸² Learning by doing, these algorithms imbued with artificial intelligence can experiment with various pricing strategies—sometimes turning a profit and sometimes taking a loss—in the process of finetuning and making the algorithm more robust.⁸³ Learning algorithms can adjust prices, perceive rival responses, and map out long-term profit-maximizing pricing strategies.⁸⁴ In addition to determining price, algorithms can also optimize production levels and storage locations.⁸⁵

Pricing algorithms can more easily carry out dynamic pricing, whereby prices change constantly in response to changing market conditions. Prices can change hundreds or thousands of times a day. Uber's surge pricing is an example of dynamic pricing.⁸⁶ With online shopping, prices can change between the moment an online shopper

(“Evidence suggests that algorithms are becoming more widespread as online retailing continues to grow.” (citing A. Cavallo, *More Amazon Effects: Online Competition and Pricing Behaviors* (Nat'l Bureau of Econ. Rsch., Working Paper No. 25138, 2018))); Graef, *supra* note 79, at 541 (“Businesses . . . commonly apply algorithms to determine what price best matches the demand and the offers of competitors. Because of the advent of big data analytics, algorithms can monitor prices more efficiently than human beings and are able to respond to market changes more quickly and accurately.”); Marco Bertini & Oded Koenigsberg, *The Pitfalls of Pricing Algorithms*, HARV. BUS. REV., Sept.–Oct. 2021, at 74, 77 (“Firms in many industries—including advertising, e-commerce, entertainment, insurance, sports, travel, and utilities—have employed dynamic pricing with varying degrees of success.”); *see also* 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, 410 (2020) (discussing how Orbitz targeted higher priced hotel options to Mac users and how Home Depot price discriminated between mobile users and desktop users).

⁸¹ Michal S. Gal & Niva Elkin-Koren, *Algorithmic Consumers*, 30 HARV. J.L. & TECH. 309, 344–45 (2017) (“[A]lgorithms . . . can automatically respond to price offers in accordance with predetermined decision parameters”); Brown & MacKay, *supra* note 80, at 7 (“Pricing algorithms used by online retailers can each be characterized as a formula to determine prices that is pre-specified by a computer program. Many online retailers consider rivals prices’ to be a key input in these calculations.”).

⁸² Emilio Calvano, Giacomo Calzolari, Vincenzo Denicolò & Sergio Pastorello, *Algorithmic Pricing: What Implications for Competition Policy?*, 55 REV. INDUS. ORG. 155, 160 (2019).

⁸³ *Id.* (“[Learning algorithms] experiment with strategies that would be sub-optimal according to their current knowledge. Experimentation is costly in that it entails, in expectation, a sacrifice of profits. However, it is valuable as it allows learning from more diverse situations.”).

⁸⁴ *See* Gal, *supra* note 7, at 78 (“Learning algorithms employ machine learning Accordingly, learning algorithms do not follow strictly static program instructions, but rather build a decision process by learning from data inputs.”).

⁸⁵ *Id.* at 79 (“Algorithms are used in a myriad of tasks, including responding rapidly to changes in demand conditions, determining efficient levels and locations for production and storage, and assessing risk levels.”).

⁸⁶ Mehra, *supra* note 7, at 1323–24.

decides to purchase and clicks the button.⁸⁷ Dynamic pricing is common,⁸⁸ though sometimes controversial.⁸⁹

Pricing algorithms are not monolithic. Firms can develop their own software programs or purchase existing algorithms, which differ in cost, speed, and other variables.⁹⁰ Pricing algorithms can consider and incorporate all manner of variables in setting individual prices.⁹¹ Moreover, the UK Competition and Markets Authority has explained:

[A] more advanced algorithm could be left to decide what data it considers is most relevant to meeting its objective (such as profit maximising). The algorithm would then act as a “black box” so that even the employees who instruct the algorithm would not know which variables it was using to set a particular price, and may not be aware of whether any increase in profit was due to attracting additional customers, charging higher prices to loyal customers, or tacit coordination.⁹²

Thus, once the pricing algorithm has been deployed, a firm using it may not be able to follow its calculations and decisions in real time.

A pricing algorithm could develop and pursue a predatory pricing strategy on its own accord, especially if it is tasked with maximizing market share or reaching a particular market share.⁹³ While this would definitely entail short-term unprofitability, a pricing algorithm has a better stomach for losses because it has no stomach. Pricing algorithms have already shown a willingness to charge irrational prices

⁸⁷ Gregory M. Stein, *Inequality in the Sharing Economy*, 85 BROOK. L. REV. 787, 823 (2020) (“Many people have experienced the frustration of having an airline seat disappear because the airline’s pricing algorithm raises the price before the buyer clicks ‘Purchase.’ Because dynamic prices move in real time, purchasers will face more surprises and will be less able to plan purchases in advance.”).

⁸⁸ Bertini & Koenigsberg, *supra* note 80, at 77 (“Firms in many industries—including advertising, e-commerce, entertainment, insurance, sports, travel, and utilities—have employed dynamic pricing with varying degrees of success.”).

⁸⁹ See *infra* note 151 and accompanying text.

⁹⁰ Gal, *supra* note 7, at 80 (“Some examples include Feedvisor’s self-learning algorithmic repricer, which uses artificial intelligence and big data techniques to set prices, or Inoptimizer, a pricing engine based on artificial intelligence and data on competitors’ and consumers’ behavior.”).

⁹¹ Bertini & Koenigsberg, *supra* note 80, at 77 (“Pricing algorithms are intended to help firms determine optimal prices on a near real-time basis. They use artificial intelligence and machine learning to weigh variables such as supply and demand, competitor pricing, and delivery time.”).

⁹² COMPETITION & MKTS. AUTH., PRICING ALGORITHMS: ECONOMIC WORKING PAPER ON THE USE OF ALGORITHMS TO FACILITATE COLLUSION AND PERSONALISED PRICING § 2.10 (2018), https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/746353/Algorithms_econ_report.pdf [<https://perma.cc/DN8F-ZJVK>].

⁹³ Cf. Gal, *supra* note 7, at 83 (“Unsupervised learning involves a process in which the algorithm autonomously determines the decisional parameters by deducing decisional rules from correlations found in the input data (such as how past pricing patterns affected profitability).”).

or disparate prices for the same item.⁹⁴ For example, Amazon’s pricing algorithm famously set a price of \$23 million for a book on the anatomy of flies.⁹⁵ A rational human price setter would never charge such a price. But humans and algorithms may approach pricing—and rationality—differently. An algorithm is much more likely to determine that price predation is a rational tactic for long-term profit maximization and stick to it.⁹⁶

B. Algorithmic Solutions to Predators’ Predicaments

Coupled with big data, algorithmic pricing makes predatory pricing significantly more feasible than imagined in the pre-internet era. After briefly explaining how each of the theoretical arguments challenging the plausibility of price predation has always been wrong, this Section explores how pricing algorithms and online sales render these old arguments particularly inapplicable to the contemporary marketplace.

1. Targeted Predation

Although theorists assume that predators will necessarily suffer asymmetric losses, this assertion has always been untrue. Even before the age of big data, Standard Oil did not lower its prices across the board when it engaged in price predation. It targeted its below-cost prices only to its rivals’ customers in order to inflict maximum injury upon its competitors while minimizing its losses. Standard Oil identified these buyers using industrial espionage, collecting relevant information from grocers, railway-freight agents, and bookkeepers of rival refiners whom Standard secretly paid.⁹⁷ The company maintained a card catalog—the analog version of a database—to keep track of which consumers to tempt with prices that seemed too good to be

⁹⁴ I’ve had the experience of looking for a particular book on Amazon and finding two copies of the same book, one for \$10 and the other more than \$900 (I always purchased the former).

⁹⁵ Sonia K. Katyal, *Private Accountability in the Age of Artificial Intelligence*, 66 UCLA L. REV. 54, 96 (2019) (“Amazon’s pricing algorithm once set the price of Peter Lawrence’s book, *The Making of a Fly*, at \$23,698,655.93 for all consumers.”).

⁹⁶ See *infra* notes 176–84 and accompanying text.

⁹⁷ RON CHERNOW, *TITAN: THE LIFE OF JOHN D. ROCKEFELLER, SR.* 256 (1998) (“Rockefeller fostered an extensive intelligence network, assembling thick card catalogs with monthly reports from field agents, showing every barrel of oil sold by independent marketers in their territory.”); U.S. BUREAU OF CORPORATIONS, *supra* note 23 at 58 (1907) (“[T]he Standard maintains an elaborate system of espionage on the business of independent concerns, in particular securing almost complete reports of their receipts and shipments of oil, by bribing railroad employees. This practice enables the Standard to direct its policy of local price cutting in the most effective manner.”).

true.⁹⁸ Standard used this data to ensure that it charged below-cost prices only to the customers of rivals, not its own customers.⁹⁹

To conceal its price predation—and to reduce potential resentment from its loyal customers, who were paying higher prices—Standard fashioned fake oil companies in the guise of independent refiners that charged extremely low (often below-cost) prices to targeted customers.¹⁰⁰ Ida Tarbell explained that each such company was “merely a Standard jobbing house which makes no oil, and which conceals its real identity under a misleading name.”¹⁰¹ Economists James A. Dalton and Louis Esposito described Standard’s strategy to monopolize the market in the American South:

Standard Oil used as many as seven bogus companies during its competition with Red C to implement this type of selective price cutting: Eureka, Eagle, Southern Oil Company of Richmond, Dixie Oil Works, Davidson Oil Company, Paragon Oil, and Home Safety Oil Delivery. Generally speaking, a bogus wagon was owned by Standard Oil but was perceived by customers as representing a marketing company independent of Standard. The purpose of a bogus wagon was to undercut the prices to customers of Standard’s rivals while allowing Standard to sell at higher prices to its own customers in the same geographic market.¹⁰²

The Potemkin firms were sometimes known to have “virtually given oil away to destroy the business of independent concerns.”¹⁰³

⁹⁸ Leslie, *supra* note 21, at 593 (“Standard maintained databases so that it knew which particular customers it should entice with below-cost prices.”); Dalton & Esposito, *supra* note 58, at 161 (“Standard maintained this information in an elaborate card catalogue that was then used to direct its sales force to capture or recapture the customers of rival refiners.”); *see also id.* at 168 (“Standard responded to the threat of losing customers by selectively reducing its prices. Standard Oil of Kentucky had developed a customer database for the geographic markets in which it operated and used it to identify customers that had defected to Red C.”).

⁹⁹ Leslie, *supra* note 21, at 593 (“According to the testimony from Standard’s own agents, Standard offered lower prices or rebates only to those buyers making purchases from independent refiners, not to Standard’s own customers.”); Dalton & Esposito, *supra* note 58, at 175 (describing testimony from Standard’s agents in Kansas City); *id.* (“H. C. Yungling testified that he was instructed to give rebates only to customers of SS&T . . .”).

¹⁰⁰ Leslie, *supra* note 21, at 593 (“Standard created these new companies as fighting brands.”); TARBELL, *supra* note 22, at 51–52 (“In these raids on peddlers of independent oil, refined oil has been sold in different cities at the doors of consumers at less than crude oil was bringing at the wells, and several cents per gallon less than it was selling to wholesale dealers in refined.”).

¹⁰¹ TARBELL, *supra* note 22, at 51.

¹⁰² Dalton & Esposito, *supra* note 58, at 169.

¹⁰³ BUREAU OF CORPORATIONS, *supra* note 97, at 438; *see also id.* (“These extraordinary cuts are perhaps most often made in the form of sales to consumers by bogus-independent concerns.”).

After Standard succeeded in driving its rival from the market, the bogus company would also depart, leaving buyers with one option: purchase oil from Standard at higher prices. Economist McGee's failure to consider Standard's ability to minimize losses associated with predation is surprising, given that it was well-known that Standard Oil created bogus companies to engage in targeted predation.¹⁰⁴ Ida Tarbell explained that when confronted with independent dealers, Standard would "threaten[] [them with] 'predatory competition,' that is, to sell at cost or less, until the rival is worn out."¹⁰⁵ If the target put up resistance, then Standard would initiate an "Oil War," the monopolist's name for predatory pricing which Standard "often intrusted to so-called 'bogus' companies, who retire when the real independent is put out of the way."¹⁰⁶ Ultimately, after the bogus companies disappeared, Standard would fill the void, charging its new customers the traditional inflated Standard price.¹⁰⁷

Standard Oil was not alone in seeing the wisdom of creating such sham companies. Dominant tobacco firms of that era also crafted counterfeit companies that appeared to be independents that charged strikingly low prices.¹⁰⁸ In the early twentieth century, the nation's sugar monopolist, the American Sugar Refining Company, pulled a similar stunt, acquiring rivals but pretending they were still independents.¹⁰⁹ In addition to forming bogus companies, dominant firms of the twentieth century also created fighting brands "whereby the monopolist would introduce a special brand, locally marketed, to foil new entry, confining sales of the brand to the entrant's local territory and withdrawing the brand as soon as the entrant left the market or sold out to the monopolist"¹¹⁰ Dominant firms in the match,

¹⁰⁴ See *supra* notes 100–03 and accompanying text.

¹⁰⁵ TARBELL, *supra* note 22, at 60.

¹⁰⁶ *Id.* at 61.

¹⁰⁷ See, e.g., Dalton & Esposito, *supra* note 58, at 175 (describing one such example of this tactic in Kansas City).

¹⁰⁸ Bolton et al., *supra* note 37, at 2245 (noting the existence of "the establishment of bogus independents, secretly controlled by the American Tobacco Company to sell at low prices in the prey's territory to force rivals to sell out at depressed prices, thereby allowing the American Tobacco Company to maintain its monopoly" (citing Malcolm R. Burns, *Predatory Pricing and the Acquisition Cost of Competitors*, 94 J. POL. ECON. 266, 271 & n.11 (1986))).

¹⁰⁹ David Genesove & Wallace Mullin, *Predation and Its Rate of Return: The Sugar Industry, 1887-1914*, 37 RAND J. ECON. 47, 63 (2006) (explaining how the American Sugar Refining Company deployed this bogus company tactic).

¹¹⁰ Bolton et al., *supra* note 37, at 2244 (discussing fighting brands in the match industry).

tobacco, and shipping industries employed versions of this tactic, which could facilitate price predation.¹¹¹

While in bygone days targeting below-cost pricing required significant investments in espionage, bribes, and expensive ruses, the internet makes it exceedingly easy to charge extremely low prices only to targeted customers. As illustrated by Standard Oil, the strategy requires two steps: identifying rivals' customers and then charging them (and only them) a predatorily low price. Pricing algorithms make each of these steps more straightforward than in decades past.

a. Identifying the Targets

First, pricing algorithms can monitor and remember shopping habits and pricing details for individual consumers in order to identify rivals' customers who would be appropriate targets for below-cost pricing.¹¹² Once recognized through URLs, internet addresses, cookies, credentials, and other identifiers, firms can track the digital trails of individual consumers.¹¹³ Some algorithms can observe, record, and analyze the prices charged by other suppliers.¹¹⁴ These algorithmic tools are improving by the day.¹¹⁵ Algorithms can also identify consumers who are most likely to switch suppliers.¹¹⁶ Big tech

¹¹¹ See, e.g., Walter Adams & James W. Brock, *Predation, "Rationality," and Judicial Somnambulance*, 64 U. CIN. L. REV. 811, 818–19 (1996) (describing the American Tobacco Company's use of fighting brands to force other tobacco companies to assent to acquisition); Leslie, *supra* note 32, at 1733 ("Fighting brands have been employed by dominant firms in the markets for photographic paper, thread, and rear projection readouts.").

¹¹² Of course, artificial intelligence is not necessary to determine willingness to pay (WTP). Firms can estimate WTP from prior dealings or observable statuses (e.g., students, senior citizens, addresses). But algorithms can collect, manage, and analyze this data far more quickly and efficiently.

¹¹³ Akiva A. Miller, *What Do We Worry About When We Worry About Price Discrimination? The Law and Ethics of Using Personal Information for Pricing*, 19 J. TECH. L. & POL'Y 41, 45 (2014) ("Online consumers can be identified using cookies, signing in to a website, using third-party credentials, and unique device identifiers. Once identified, consumers are tracked through the endless digital trail they leave behind.").

¹¹⁴ Gal & Elkin-Koren, *supra* note 81, at 344 ("[A]lgorithms can quickly and efficiently observe prices offered by suppliers to other consumers or remember offers made by suppliers in the past . . ."); see also Brown & MacKay, *supra* note 80, at 3 ("Online markets have allowed retailers to gather high-frequency data on rivals' prices and react quickly through the use of automated software.").

¹¹⁵ Pascale Chapdelaine, *Algorithmic Personalized Pricing*, 17 N.Y.U. J.L. & Bus. 1, 18 (2020) ("[T]he rapidly improving quality of behavioral predictive algorithmic tools, enabl[es] more effective and targeted personalized pricing . . .").

¹¹⁶ The UK Competition and Markets Authority explained: "[I]t is possible that incumbent firms may use . . . data, algorithms and techniques for personalised pricing in order to identify and selectively target those customers most at risk of switching, or who are otherwise crucial to a new competitor. This could make it easier . . . for incumbent firms to predate successfully . . ." Competition and Markets Authority, *Algorithms: How*

firms may even be able to determine a consumer's reservation price by eavesdropping through her personal digital assistant, such as Alexa or Siri.¹¹⁷

Even brick-and-mortar stores can use AI technology to identify the reservation prices of individual consumers. Bringing James Bond-style gadgetry to malls and main streets, retailers can follow customers using facial recognition technology and in-store cameras in ceilings, mannequins, and on employees' lapels.¹¹⁸ Sophisticated stores can track browsers and buyers through their cellphones and radio frequency identification tags.¹¹⁹ Retailers track consumers to build individual profiles, but the data collection is not limited to shopping habits.¹²⁰ Some stores are already using and experimenting with these

They Can Reduce Competition and Harm Consumers, GOV.UK (Jan. 19, 2021), <https://www.gov.uk/government/publications/algorithms-how-they-can-reduce-competition-and-harm-consumers/algorithms-how-they-can-reduce-competition-and-harm-consumers> [https://perma.cc/G6WJ-7WER].

¹¹⁷ Maurice E. Stucke & Ariel Ezrachi, *How Digital Assistants Can Harm Our Economy, Privacy, and Democracy*, 32 BERKELEY TECH. L.J. 1239, 1265 (2017) ("Given its ubiquity in the home, a digital assistant will have even more personal data, more opportunities to observe how users respond to different advertisements, pricing, and products, and more opportunities to learn the right price point for that user."); Gerhard Wagner & Horst Eidenmüller, *Down by Algorithms? Siphoning Rents, Exploiting Biases, and Shaping Preferences: Regulating the Dark Side of Personalized Transactions*, 86 U. CHI. L. REV. 581, 586 (2019) ("Your personal digital assistant—Amazon's Alexa or Apple's Siri—may prove to be a 'devious' agent, eavesdropping on conversations about your urgent desires in what used to be your private sphere.") (citing Ariel Ezrachi & Maurice E. Stucke, *Is Your Digital Assistant Devious?* *16 (Univ. of Tenn. Knoxville Coll. of L. Legal Studies Research Paper No. 304, 2016), <https://ssrn.com/abstract=2828117> [https://perma.cc/3GU8-SZ8L]).

¹¹⁸ Miller, *supra* note 113, at 45; *see also* TUROW, *supra* note 73, at 236–37 (discussing retailer use of facial recognition software).

¹¹⁹ Miller, *supra* note 113, at 45; *see also* Chapdelaine, *supra* note 115, at 13 ("[B]rick and mortar stores personaliz[e] price offerings to in-store consumers by scanning their cellphones.").

¹²⁰ Target, for example, assigns its shoppers a Guest ID number that it uses to profile its customers, monitoring what they buy, when they use store coupons or refunds, call the customer helpline, open Target e-mails, or visit Target's website. Target builds its individual profiles to include (among other details) each individual's age, marital status, estimated salary, websites visited, as well as "your ethnicity, job history, the magazines you read, if you've ever declared bankruptcy or got divorced, the year you bought (or lost) your house, where you went to college, what kinds of topics you talk about online, whether you prefer certain brands of coffee, paper towels, cereal or applesauce . . ." EZRACHI & STUCKE, *supra* note 5, at 92 (quoting Charles Duhigg, *How Companies Learn Your Secrets*, N.Y. TIMES MAG. (Feb. 16, 2012), <https://www.nytimes.com/2012/02/19/magazine/shopping-habits.html> [https://perma.cc/NG25-5ZLT]). Target customers (unknowingly) consent to being tracked wherever they are and to allowing Target to access their Facebook ID, their friends' IDs, their profile pictures, and their postings in any public forum, such as Facebook and chat rooms. *Id.*

technologies.¹²¹ And this tracking technology will undoubtedly grow more advanced.¹²²

Consumer data has become a market unto itself. Firms can purchase data that identifies consumers as well as their browsing, consumption, and spending habits. Firms with sufficient resources can “obtain data on individual consumers—such as their location, device and browser used for orders, and browsing and shopping history—that allow firms to assess each individual consumer’s reservation price for a particular product or service.”¹²³ The prospect of price predation increases the value of consumer data. A firm with big data is better positioned to employ targeted algorithmic predatory pricing, as the following discussion explores.¹²⁴

b. Algorithmic Price Discrimination

Second, after firms identify individual consumers and their purchase histories, pricing algorithms can deliver personalized pricing,¹²⁵ which allows firms to price discriminate generally and to target below-cost prices in particular. Although price discrimination can take many forms,¹²⁶ this Article uses the phrase “price discrimina-

¹²¹ See Oren Bar-Gill, *Algorithmic Price Discrimination When Demand Is a Function of Both Preferences and (Mis)perceptions*, 86 U. CHI. L. REV. 217, 226 (2019). Some retailers combine in-person and internet sleuthing. For example, pursuant to the small print in its privacy policy, customers of Ulta Beauty, a cosmetics chain, unwittingly agree to allow the retailer to track them online to non-Ulta sites and to “track[] members’ locations via their mobile devices without requesting explicit permission,” among other invasions of privacy. TUROW, *supra* note 73, at 166. Ulta uses this data, in part, to steer the customer’s in-store experience toward increased purchases. *Id.* at 166–67.

¹²² TUROW, *supra* note 73, at 241 (“We are only at the beginning of this retailing transformation. Many of the data collection and tracking technologies that will become standard likely have yet to be invented . . .”).

¹²³ Wagner & Eidenmüller, *supra* note 117, at 586.

¹²⁴ Amazon provides a clear example of how online firms can harvest and analyze consumer data. Because Amazon is both a platform and a seller, Amazon often knows what its rivals are charging for particular products to individual customers.

¹²⁵ Alan M. Sears, *The Limits of Online Price Discrimination in Europe*, 21 COLUM. SCI. & TECH. L. REV. 1, 7 (2019) (“Behavioral targeting, and in turn price discrimination (or more specifically personalized pricing), often rely on algorithms, not only to categorize consumers, but also to determine the price to display to consumers.”).

¹²⁶ In economics, the phrase “price discrimination” can refer to three different pricing strategies. First-degree price discrimination refers to sellers knowing each consumer’s WTP and charging that precise amount; each consumer receives an individualized price. In third-degree price discrimination, the seller places consumers into groups based on their perceived WTP (e.g., low WTP, medium WTP, and high WTP) and then charges a different price based on which group a consumer is in, e.g., charging less to students or senior citizens. In second-degree price discrimination, the seller distinguishes among consumers by varying product offerings, for example charging lower prices for matinees, paperback books, and round-trip airline tickets that include a weekend stay. Marcel Kahan & Ehud Kamar, *Price Discrimination in the Market for Corporate Law*, 86 CORNELL L.

tion” informally to refer to the practice of a seller charging different prices to different consumers based on a consumer’s perceived willingness to pay (WTP). Through the tailored use of predatory pricing algorithms, a firm can offer below-cost prices to those consumers who are currently customers of the firm’s rivals, while continuing to charge profitable prices to the firm’s already loyal customers. AI can determine an individual consumer’s maximum price (i.e., their WTP).¹²⁷ Pricing algorithms facilitate price discrimination, by which different consumers are charged different prices, usually mapped to their WTP.¹²⁸ Uber’s pricing algorithm, for example, has been shown to charge different prices to different customers who are in the same surge zone at the same time.¹²⁹ Pricing algorithms can even undertake dynamic price discrimination, changing personalized prices quickly.¹³⁰

REV. 1205, 1215–17 (2001). Pricing algorithms hold the potential of allowing firms to come closer to first-degree price discrimination. Gautier et al., *supra* note 80, at 406 (“[S]everal models proposed in scientific literature have indeed . . . shown [AI-enabled pricing algorithms] to be able to price discriminate at a finer degree of granularity.” (citations omitted)). But even without perfect price discrimination, algorithms can better effectuate third-degree price discrimination, which would also facilitate targeted predation and recoupment.

¹²⁷ Charles A. Miller, *Big Data and the Non-Horizontal Merger Guidelines*, 107 CALIF. L. REV. 309, 340 (2019) (“Behavioral data and machine learning analysis may allow firms to accurately predict consumers’ maximum willingness to pay and alter pricing accordingly via complex pricing algorithms.”); *see also* MAURICE E. STUCKE & ALLEN P. GRUNES, *BIG DATA AND COMPETITION POLICY* 186–87 (2016) (noting how algorithms can “predict[] individual tastes and preferences from the variety of personal data the company collects across its platform (such as the person’s email, geo-location data, social network, browser history) and Internet (from the cookies placed when the person visits a website).”).

¹²⁸ Ryan Calo & Alex Rosenblat, *The Taking Economy: Uber, Information, and Power*, 117 COLUM. L. REV. 1623, 1657 (2017) (“Algorithmic pricing is also evident in other businesses, . . . which use customers’ information, such as their location comparable to other available retail options or their demographic, to target them with different prices for the same items.”); EZRACHI & STUCKE, *supra* note 5, at 100 (“[W]ith advances in pricing algorithms and the collection of a greater variety and volume of personal data, online companies can more closely approximate our reservation price. They may find the road to perfect price discrimination and increased profits irresistible.”); Thomas K. Cheng & Julian Nowag, *Algorithmic Predation and Exclusion*, 25 U. PA. J. BUS. L. 41, 51 (2023) (“Algorithmic targeting would allow the dominant firm to target its below-cost price cuts at the marginal customers while leaving the prices for its inframarginal customers untouched.”).

¹²⁹ *See* Calo & Rosenblat, *supra* note 128, at 1658 (“[C]omputer scientists . . . measured the prices Uber’s Application Programming Interface returned for surge in various areas to various passengers and examined those prices against the prices passengers actually received. They found a discrepancy, with users in the same surge zone at the same time receiving different prices”) (citing Le Chen, Alan Mislove & Christo Wilson, *Peeking Beneath the Hood of Uber*, 2015 PROC. OF THE 2015 INTERNET MEASUREMENT CONF. 495, 495–96, <https://dl.acm.org/doi/10.1145/2815675.2815681> [<https://perma.cc/N4PG-MUP2>]).

¹³⁰ *See* Miller, *supra* note 113, at 47 (“While not all dynamic pricing is personally targeted, it is possible to tailor posted prices to individual buyers online.”) (citing Anita Ramasastry, *Web Sites Change Prices Based on Customers’ Habits*, CNN (June 24, 2005,

Pricing algorithms are both faster and more accurate than human price setters.¹³¹ Algorithms can determine what price each individual consumer sees on a website.¹³² They can—and do—hide the lowest prices from consumers with higher WTP.¹³³

Retailers can also use targeted advertising and coupons to facilitate individualized pricing. Algorithms analyze data to discern the WTP of individual consumers and target them with ads and lower prices than those offered to consumers with a higher WTP.¹³⁴ These ads can be accompanied or followed by customer-specific coupons that produce personal prices.¹³⁵ Based on their usage, these electronic

3:14 PM), <https://edition.cnn.com/2005/LAW/06/24/ramasastry.website.prices> [<https://perma.cc/29RA-VLP4>]; see also OECD, *supra* note 75, at 16 (“Given their automated nature, pricing algorithms are particularly useful to implement continuous price changes over time – dynamic pricing – or to charge different prices to consumers based on their personal characteristics – price discrimination.”); Ezrachi & Stucke, *supra* note 7, at 1780 (“Online trade platforms enable sellers to segment the market by using dynamic pricing.”).

¹³¹ See Brown & MacKay, *supra* note 80, at 7 (“Algorithms facilitate both regular and more frequent updates, as software can better monitor rivals’ prices and can find the solution to a difficult pricing problem more efficiently than a human agent. [H]uman agents can be slow and error-prone, and they cannot be expected to maintain a regular pricing frequency.”).

¹³² See Sears, *supra* note 125, at 7 (“Behavioral targeting may also be used in ranking algorithms that result in ‘price steering.’ Price steering is ‘personalizing search results to place more or less expensive products at the top of the list.’” (quoting Aniko Hannak, Gary Soeller, David Lazer, Alan Mislove & Christo Wilson, *Measuring Price Discrimination and Steering on E-Commerce Web Sites*, 2014 PROC. OF THE 2014 INTERNET MEASUREMENT CONF. 305, 309, <https://dl.acm.org/doi/pdf/10.1145/2663716.2663744> [<https://perma.cc/EFQ5-JP8B>])).

¹³³ See Jamie L. Williams, *Automation Is Not “Hacking”: Why Courts Must Reject Attempts to Use the CFAA as an Anti-Competitive Sword*, 24 B.U. J. SCI. & TECH. L. 416, 445–46 (2018) (“ProPublica journalists have investigated Amazon’s algorithm for ranking products by price via a ‘software program that simulated a non-Prime Amazon member’ and ‘scraped . . . product listing page[s]’; their research uncovered that Amazon’s pricing algorithm was hiding the best deals from many of its customers.” (citing Julia Angwin & Surya Mattu, *How We Analyzed Amazon’s Shopping Algorithm*, PROPUBLICA (Sept. 20, 2016, 8:00 AM)), <https://www.propublica.org/article/how-we-analyzed-amazons-shopping-algorithm> [<https://perma.cc/5H6Y-2NUX>]). In theory, price discrimination can be thwarted by arbitrage, in which a customer with a personally low WTP purchases the product at a cheap price and then resells it at a markup to another customer with a high WTP, thus undercutting the monopolist’s price. But pricing algorithms can stop arbitrage by identifying and blocking sales to arbitrageurs. Ramsi A. Woodcock, *Big Data, Price Discrimination, and Antitrust*, 68 HASTINGS L.J. 1371, 1387 (2017) (“[B]ig data will also permit firms to eliminate the arbitrage problem because it will allow them to identify, and cut off, low-price buyers who resell the product.”).

¹³⁴ See Wagner & Eidenmüller, *supra* note 117, at 582 (“Smart sales algorithms are used to market products and services, microtargeting idiosyncratic consumer preferences with personalized offers.”).

¹³⁵ Miller, *supra* note 113, at 46 (“By offering discount coupons along with a targeted ad, sellers can price discriminate between loyal self-selected shoppers who sign up for special offers and other potential customers who did not.”); EZRACHI & STUCKE, *supra* note 5, at 91 (“Even coupons are becoming more personalized and targeted. One example

coupons, in turn, help build more accurate profiles for individual consumers.¹³⁶ A predatory firm can use targeted coupons to offer low prices only to the current customers of its rivals, not its loyal customers.¹³⁷ Under this approach, a firm can set a high shelf price and then have its algorithm offer rebates and discounts only to those consumers whose WTP the algorithm has calculated to be low.

Even brick-and-mortar stores are using algorithms to price discriminate. Some stores use personalized (sometimes digital) coupons based on collected data.¹³⁸ Being even more dynamic, “B&Q, a British multinational company, tested in its brick-and-mortar stores digital price tags that interfaced with customers’ phones and adjusted the displayed price based on the customer’s loyalty card data and spending habits.”¹³⁹ Back in 2013, Safeway’s CEO predicted that “[t]here’s going to come a point where our shelf pricing is pretty irrelevant because we can be so personalized in what we offer people.”¹⁴⁰ In some of its Amazon Fresh and Whole Foods Markets, Amazon has begun implementing “Just Walk Out” technology, which uses cameras and sensors to track what shoppers have put in their carts and then charges shoppers as they exit the store without the need for either a cashier or checkout line.¹⁴¹ This technology facilitates personalized pricing. In 2020, IKEA began charging different prices to consumers in its Dubai store, based on how long the consumer traveled to get

is Coupons.com, an online platform that in 2015 delivered personalized promotions every month to approximately 17 million consumers.”).

¹³⁶ See Miller, *supra* note 113, at 46 (“Electronic coupons are built to surreptitiously transmit a large amount of consumer information directly to the seller and are used alongside data-mining tools to experiment with prices and discover information about consumers’ shopping patterns.”).

¹³⁷ See Gautier et al., *supra* note 80, at 409 (“[F]irms can display a flat price online but offer targeted coupons to consumers.”).

¹³⁸ Lina M. Khan, *Amazon’s Antitrust Paradox*, 126 YALE L.J. 710, 764 (2017) (“It is true that brick-and-mortar stores also collect data on customer purchasing habits and send personalized coupons.”); Bar-Gill, *supra* note 121, at 226 (“Grocery stores are personalizing pricing using digital coupons.”). This strategy has been around for over three decades. See TUROW, *supra* note 73, at 86 (“Progressive Grocer estimated in 1991 that 12 percent of the seventeen thousand chain stores and 3 percent of independent grocers offered some sort of electronic coupon program at checkout. Many tried tailoring those coupons to the purchaser’s buying habits.”).

¹³⁹ Bar-Gill, *supra* note 121, at 226.

¹⁴⁰ Candice Choi, *How Grocery Store Loyalty Programs Affect What You Buy, How Much You Spend*, BOS. GLOBE (May 17, 2013, 12:00 AM), <https://www.bostonglobe.com/business/2013/05/16/how-grocery-store-loyalty-programs-affect-what-you-buy-how-much-you-spend/8xTOlirUcBDctXrxSQI3TK/story.html> [https://perma.cc/4EXL-C99S] (quoting Steve Burd, CEO of Safeway).

¹⁴¹ Annie Palmer, *Amazon Brings its Cashierless Tech to Two Whole Foods Stores*, CNBC (Sept. 8, 2021, 8:16 AM), <https://www.cnbc.com/2021/09/08/amazon-brings-its-cashierless-tech-to-two-whole-foods-stores.html> [https://perma.cc/C6B9-T39U].

there.¹⁴² Upon checking out, an IKEA “cashier would run an algorithm that factored time spent, distance traveled, and the average hourly wage of a Dubai worker to calculate the monetary value of the ride. The store then offered that value as a form of currency.”¹⁴³ This pricing algorithm created more personalized pricing without performing dynamic pricing. Dynamic pricing was traditionally difficult for brick-and-mortar stores because tangible price tags had to be physically changed.¹⁴⁴ But personalized electronic coupons allow stores to post a base price and then give consumers individualized discounts based on an algorithm’s output, allowing pricing algorithms to engage in dynamic pricing in brick-and-mortar stores.¹⁴⁵ Coupled with in-store beacons that track shoppers through their smartphones, retailers can send individual consumers personalized coupons.¹⁴⁶ In short, personalized pricing currently allows for price discrimination.¹⁴⁷

John D. Rockefeller, the founder of Standard Oil and the richest person in America,¹⁴⁸ used ploys like bogus companies to price discriminate with targeted below-cost prices, in part, to avoid backlash from Standard Oil customers who were being charged monopoly prices.¹⁴⁹ Today, firms using personalized pricing also face the poten-

¹⁴² Bertini & Koenigsberg, *supra* note 80, at 78–79.

¹⁴³ *Id.*

¹⁴⁴ Jeffrey Dastin, *How Amazon is Crushing Rivals Like Walmart in a Burgeoning Tech War Over the Future of Retail*, BUS. INSIDER (May 10, 2017, 2:12 PM), <https://www.businessinsider.com/how-amazon-beats-rivals-like-walmart-with-bots-to-match-price-cuts-2017-5> [<https://perma.cc/GV8J-FL9W>] (“Traditionally, brick-and-mortar stores changed prices no more than weekly because of the time and expense needed to swap labels by hand.”); *see also* Ezrachi & Stucke, *supra* note 7, at 1780 (“When we were growing up, humans monitored market activity and determined whether, and by how much, to raise or lower prices, and physically stamped products with price stickers. We recall the clerks along the supermarket aisle stamping each food can. Pricing decisions took weeks—if not months—to implement.”).

¹⁴⁵ *See* Mehra, *supra* note 7, at 1327 (“Sellers use dynamic-pricing algorithms to gauge supply and demand and set prices not only for books and air tickets online, but increasingly, for consumer electronics, groceries, and other tangible goods in brick-and-mortar stores.”).

¹⁴⁶ *See* TUROW, *supra* note 73, at 1–2 (“If shoppers carry the right apps on their smartphones and have the correct technology turned on, the beacons will alert the merchants and they can send the shoppers personalized coupons or other messages associated with the goods in a beacon’s proximity.”).

¹⁴⁷ *See* Salil K. Mehra, *Data Privacy and Antitrust in Comparative Perspective*, 53 CORNELL INT’L L.J. 133, 139 (2020) (“[T]he ability to gather data on individual consumers, process it algorithmically, and set prices automatically, has driven Silicon Valley to invest in technologically oriented economists in order to develop and spread price discrimination strategies.”).

¹⁴⁸ Steve Hargreaves, *The Richest Americans in History*, CNN (June 2, 2014, 6:18 PM), <https://money.cnn.com/gallery/luxury/2014/06/01/richest-americans-in-history> [<https://perma.cc/9ABB-9S7D>] (calculating that Rockefeller is the richest American ever).

¹⁴⁹ *See supra* notes 100–07 and accompanying text.

tial wrath of consumers, the vast majority of whom hate price discrimination.¹⁵⁰ Consumers may also resist certain forms of dynamic pricing. For example, the Coca-Cola Company was forced to abandon its experiment with temperature-sensitive vending machines, which raised prices with the outside temperature, in response to consumer protests.¹⁵¹

Because of the risk of consumer backlash, some commentators view concealment as a prerequisite for personalized pricing.¹⁵² Online sellers can, however, disguise their price discrimination.¹⁵³ Firms can, for example, conceal the low internet prices offered to select consumers.¹⁵⁴ The algorithms themselves are generally opaque, preventing consumers from directly discerning whether they are being charged a higher price than other consumers.¹⁵⁵ Digital coupons allow both online and brick-and-mortar firms to conceal price discrimina-

¹⁵⁰ Chapdelaine, *supra* note 115, at 19 (“Available consumer surveys indicate a strong consumer dislike of discriminatory pricing. In one survey of 1500 American households published in 2005, 91% of respondents were strongly against retailers charging different prices for the same product based on the collection of personal information.” (citing Joseph Turow, Lauren Feldman & Kimberly Meltzer, *Open to Exploitation: America’s Shoppers Online and Offline* 22 (A Rep. from the Annenberg Pub. Pol’y Ctr. of the Univ. of Pa., Working Paper, 2005))), https://repository.upenn.edu/asc_papers/35 [<https://perma.cc/8AQT-3ZNT>]; David Streitfeld, *Test of “Dynamic Pricing” Angers Amazon Customers*, WASH. POST (Sept. 27, 2000), <https://www.washingtonpost.com/archive/politics/2000/09/27/on-the-web-price-tags-blur/14daea51-3a64-488f-8e6b-c1a3654773da> [<https://perma.cc/9FK4-YNWD>]; EZRACHI & STUCKE, *supra* note 5, at 123–24 (reporting data on how majority of consumers believe that price discrimination is unethical and illegal).

¹⁵¹ Bertini & Koenigsberg, *supra* note 80, at 77 (“A classic and well-known example is Coca-Cola, which experimented in the late 1990s with temperature-sensitive vending machines that would increase the price of a beverage on a hot day. The company quickly abandoned the project in the wake of public outrage.”). *Cf.* Calo & Rosenblat, *supra* note 128, at 1656 (“Uber researchers found that individuals are more willing to pay surge pricing when the batteries on their phones are low.”).

¹⁵² Chapdelaine, *supra* note 115, at 17 (“[T]he ability to conceal the occurrence of personalized pricing is another precondition for suppliers to have recourse to this practice.”); *see also* Khan, *supra* note 138, at 763 (“A major topic of discussion at the 2014 National Retail Federation annual convention, for example, was how to introduce discriminatory pricing without triggering consumer backlash.”).

¹⁵³ Chapdelaine, *supra* note 115, at 18 (noting “the relative ease with which this commercial practice may be concealed”); *see also* McSweeney & O’Dea, *supra* note 7, at 80 n.31 (predicting companies will “camouflage online price discrimination”).

¹⁵⁴ Miller, *supra* note 113, at 79 (“Sellers find ways to avoid publicly posting their lowest prices in order to circumvent automated search bots that deliver low prices to comparison-shopping sites.” (citing P.K. Kannan & Praveen K. Kopalle, *Dynamic Pricing on the Internet: Importance and Implications for Consumer Behavior*, 5 INT’L J. ELEC. COM. 63, 70 (2001))).

¹⁵⁵ Miller, *supra* note 127, at 340 (“Because of the complexity of these algorithms, consumers may be unable to determine when they are being discriminated against.”).

tion to some extent, in that every consumer sees the same shelf price.¹⁵⁶

Given their objections to price discrimination, consumers may try to thwart algorithms by disguising their online identities.¹⁵⁷ Sophisticated consumers can manipulate their digital profiles to make their WTP seem lower.¹⁵⁸ Wary but less tech-savvy consumers may acquire specialized software that misrepresents users' identities online in order to evade personalized pricing.¹⁵⁹ These ploys are designed either to conceal consumers' identities entirely or to create fake ones,¹⁶⁰ like a consumer version of the bogus companies that Standard and other predators used to price predate in the early twentieth century.¹⁶¹

Such consumer countermeasures, however, are not completely effective. First, it bears noting that many—perhaps most—consumers are unaware of or indifferent to this tracking and will offer no resistance.¹⁶² Second, many internet users will find it inconvenient and sometimes infeasible to disallow tracking cookies.¹⁶³ Third, even

¹⁵⁶ See Lina Khan, *Why You Might Pay More than Your Neighbor for the Same Bottle of Salad Dressing*, QUARTZ (Jan. 19, 2014), <https://qz.com/168314/why-you-might-pay-more-than-your-neighbor-for-the-same-bottle-of-salad-dressing> [https://perma.cc/KVL3-QCBC] (“‘Coupons will be the doorway in to differential pricing,’ said Scott Anderson, principal consultant at FICO, which provides data analytics and decision-making services. In other words, we could all end up paying significantly different amounts for the same items, even if we see the same prices while browsing.”).

¹⁵⁷ Gal, *supra* note 7, at 92 (“[I]n order to avoid personalized pricing, consumers might prefer to browse anonymously.”); Gautier et al., *supra* note 80, at 425 (noting that some consumers “act strategically and regulate their online behavior in order to distort the personal data that they disclose or hinder its harvesting”).

¹⁵⁸ See Wagner & Eidenmüller, *supra* note 117, at 589 n.23 (“Super-savvy strategic consumers might also try to trick the algorithms by manipulating their digital profile, etc.”).

¹⁵⁹ *Id.* at 588 (“Given that consumers regard personalized prices as highly unfair, they will attempt to avert the harm suffered using self-help remedies. Consumers may try to achieve anonymity vis-à-vis businesses. Both software and hardware tools—such as Tor and Anonabox—can be employed to this effect.”).

¹⁶⁰ Miller, *supra* note 113, at 88–89 (“Other technologies could also allow consumers to avoid price discrimination by allowing them to shop anonymously or with a fake identity.” (citing Alessandro Acquisti & Hal R. Varian, *Conditioning Prices on Purchase History*, 24 *MKTG. SCI.* 367, 367–68 (2005))).

¹⁶¹ See *supra* notes 100–11 and accompanying text.

¹⁶² See TUROW, *supra* note 73, at 249 (“A 2014 Yahoo! report, for example, concluded that when Americans are online they ‘demonstrate a willingness to share information, as more consumers begin to recognize the value and self-benefit of allowing advertisers to use their data in the right way.’” (quoting Yahoo!, *The Balancing Act: Getting Personalization Right* (May 2014), https://kipdf.com/the-balancing-act-getting-personalization-right-may-the-balancing-act-presented-_5aeb81457f8b9ac9298b45e0.html [https://perma.cc/8DEP-VF9F])).

¹⁶³ See Wagner & Eidenmüller, *supra* note 117, at 589 (“[D]isallowing tracking cookies may come at the (opportunity) cost of being shut out of certain transactions.”).

software programs designed to get consumers low prices on the internet can allow or facilitate personalized pricing.¹⁶⁴ Moreover, many consumers may not be able to afford even this inadequate technology. Fourth, sellers will develop or purchase their own tools to circumvent consumer efforts to conceal their identities and reservation prices.¹⁶⁵ Online sellers can also employ strategies that circumvent price-comparison tools.¹⁶⁶ An inefficient arms race between anonymity-seeking consumers and sleuthing sellers ensues, as buyers hide and sellers seek.¹⁶⁷ Having more at stake, and armed with resources, sellers are likely to win the war, even if some savvy consumers sometimes win a battle or two. Appreciating this dynamic, many rational consumers will preemptively surrender and not undertake efforts to protect their privacy against retailers.¹⁶⁸

Algorithmic personalized pricing is not merely inevitable; it is already here. From airlines to hardware stores, online businesses are already charging individualized prices.¹⁶⁹ The practice is now well-established on the internet.¹⁷⁰ Amazon notably charges higher prices

¹⁶⁴ *Id.* (“ShadowBid purportedly gets consumers the best price available on Amazon. But this price may either still be a personalized price or, if the bid is made anonymously, not the lowest price available elsewhere, thereby asking consumers to pay more than they want to.”).

¹⁶⁵ Miller, *supra* note 113, at 67.

¹⁶⁶ *Id.* at 79 (“One way new pricing strategies undermine savvy shoppers is by making price-comparison tools less effective.” (citing Kannan & Kopalle, *supra* note 154, at 70)).

¹⁶⁷ *Id.* at 67 (“Buyers who could be adversely treated might wish to invest time, effort, and money in anonymizing technologies and to forego certain online activities in order to protect their anonymity and avoid negative price discrimination. Sellers, in turn, might invest money and effort in order to thwart these anonymizing methods.”).

¹⁶⁸ See TUROW, *supra* note 73, at 255 (“When it comes to protecting personal data, our survey found those with the knowledge to accurately calculate the costs and benefits of maintaining privacy are likely to consider their efforts to do so futile.”). Moreover, some consumers may favor being tracked because they prefer receiving personalized ads and coupons.

¹⁶⁹ Chapdelaine, *supra* note 115, at 13 (“Customer anecdotes, reports, and empirical studies show signs of algorithmic personalized pricing taking place”); Miller, *supra* note 113, at 53 (“By identifying the location of online shoppers, chain stores like Staples and Home Depot can offer higher prices to shoppers who live far from the their competitors’ stores. This tactic . . . benefits people living in high-income areas with more shopping venues over those in lower-income areas with fewer shopping options.” (citing Jennifer Valentino-Devries, Jeremy Singer-Vine & Ashkan Soltani, *Websites Vary Prices, Deals Based on Users’ Information*, WALL ST. J. (Dec. 24, 2012, 12:01 AM), <https://www.wsj.com/articles/SB10001424127887323777204578189391813881534> [<https://perma.cc/ST8H-AYE6>])).

¹⁷⁰ See Wagner & Eidenmüller, *supra* note 117, at 586 (“In 2014, researchers used the accounts and cookies of over three hundred real-world users to detect price steering and discrimination on sixteen popular e-commerce sites. They found evidence of some form of personalization on nine of these sites.” (citing Aniko Hannak, Gary Soeller, David Lazer, Alan Mislove & Christo Wilson, *Measuring Price Discrimination and Steering on E-*

to its regular customers.¹⁷¹ This ability to price discriminate has important implications for predatory pricing. If a dominant firm can charge a below-cost price to its rivals' customers while charging a competitive (or supracompetitive) price to its existing customers, predatory pricing becomes much more feasible.

Ultimately, the theory that price predators must take losses on all their sales was always wrong, disproven by the Standard Oil and other early-era predatory schemes long before economists made the demonstrably false assumption that a price predator must incur asymmetric losses. In the AI era, the assumption's falsity increases with each passing day. Algorithmically targeted below-cost pricing significantly reduces the cost of predatory pricing schemes and therefore renders them more plausible. Moreover, AI allows firms to engage in price discrimination at an enormous scale, setting truly personalized prices for large numbers of individual consumers.¹⁷² In sum, pricing algorithms solve the problem of asymmetric losses that theorists have posited to make predatory pricing seem implausible.

2. *Algorithmic Commitment*

Although many scholars argue that predatory pricing threats are not credible because the predator cannot convincingly commit to charging a below-cost price,¹⁷³ even before the age of algorithms, this assertion was wrong. Predatory firms can communicate their commitment to below-cost pricing by actually engaging in below-cost pricing and making their competitors aware of it.¹⁷⁴ By undertaking predatory

Commerce, 2014 PROC. OF THE 2014 INTERNET MEASUREMENT CONF. 305, 317, <https://dl.acm.org/doi/pdf/10.1145/2663716.2663744> [<https://perma.cc/EFQ5-JP8B>]).

¹⁷¹ Chapdelaine, *supra* note 115, at 13 (“Customer anecdotes, reports, and empirical studies show signs of algorithmic personalized pricing taking place—Amazon selling products to regular customers at higher prices than to others . . .”); Gautier et al., *supra* note 80, at 409–10 (noting Amazon charging more for DVDs and mahjong tiles to existing customers).

¹⁷² Wagner & Eidenmüller, *supra* note 117, at 582–83 (“Big data and artificial intelligence may enable businesses to exploit informational asymmetries and/or consumer biases in novel ways and on an unprecedented scale.”).

¹⁷³ See *supra* notes 49–51 and accompanying text.

¹⁷⁴ See Leslie, *supra* note 40, at 302–05 (describing historical examples of firms engaging in predatory pricing to establish the credibility of their threats of continued predation); Oliver E. Williamson, *Predatory Pricing: A Strategic and Welfare Analysis*, 87 YALE L.J. 284, 287 (1977) (“If by responding aggressively to a current threat of entry a dominant firm can give a ‘signal’ that it intends to react vigorously to entry in later time periods or different geographical regions, discounted future gains may more than offset sacrifices of current profit.”).

pricing, firms acquire a reputation for predation that makes their future threats much more credible.¹⁷⁵

Algorithmic pricing further undermines the so-called commitment canard. These AI-enabled decisionmakers can immediately and automatically undercut rivals' prices.¹⁷⁶ Pricing algorithms can “work with a huge amount of data, unimaginably fast, without interruptions, without emotions, and increasingly also without human involvement.”¹⁷⁷ Economists have demonstrated how pricing algorithms can help firms communicate commitment to pricing strategies in the context of collusion.¹⁷⁸ That same commitment can serve predatory purposes.¹⁷⁹

A pricing algorithm can exhibit greater commitment than human price setters by automatically reacting to rivals' price changes.¹⁸⁰ Pricing algorithms may be more credible in part because they do not experience fear.¹⁸¹ Managers concerned about their jobs may cease price predation when losses pile up, but algorithms do not worry about job security or their existential survival (Hal 9000 from *2001: A Space Odyssey* excepted¹⁸²). Pricing algorithms can commit to low prices that appear irrational, and they do not deviate.¹⁸³ This automation demonstrates commitment.¹⁸⁴

¹⁷⁵ Leslie, *supra* note 40, at 298–300 (explaining how and why “some firms actively hone reputations for being overly aggressive against competitors”).

¹⁷⁶ Gal & Elkin-Koren, *supra* note 81, at 345 (noting that algorithms “can automatically respond to price offers in accordance with predetermined decision parameters”).

¹⁷⁷ Václav Šmejkal, *Cartels by Robots - Current Antitrust Law in Search of an Answer*, 4 INTEREULAWEST: J. INT'L & EUR. L., ECON. & MKT. INTEGRATIONS 1, 3 (2017).

¹⁷⁸ Brown & MacKay, *supra* note 80, at 6 (“We consider algorithms to be an economic mechanism to make such commitments credible.”).

¹⁷⁹ See MacKay & Weinstein, *supra* note 76, at 141 (“[A]lgorithms provide firms with the ability to commit to a set of (inflexible) rules when determining prices.”).

¹⁸⁰ Brown & MacKay, *supra* note 80, at 7; *id.* at 116 n.24 (“[A]n algorithm provides a short-run commitment device to a pricing strategy. When an algorithm depends on rivals' prices, it can autonomously react to price changes by rivals according to the formula encoded by the computer program.”); see also MacKay & Weinstein, *supra* note 76, at 116 (“Algorithms typically encode in software a set of instructions to update prices, and this software is used to update prices many times before the instructions are changed. In this way, the algorithm allows a firm to commit to a pricing strategy in advance.”).

¹⁸¹ See Gal, *supra* note 7, at 84 (“The fact that algorithms—unless their developers code them otherwise—make rational decisions, devoid of ego and biases, also potentially eases coordination, by making their decisions more predictable.”).

¹⁸² *2001: A SPACE ODYSSEY* (Metro-Goldwyn-Mayer & Stanley Kubrick Productions 1968).

¹⁸³ See EZRACHI & STUCKE, *supra* note 5, at 77 (“Unlike humans, the computer does not fear detection and possible financial penalties or incarceration; nor does it respond in anger.”).

¹⁸⁴ Cf. Brown & MacKay, *supra* note 80, at 1 (“Algorithms can change pricing behavior by enabling firms to update prices more frequently and automate pricing decisions. Thus, firms can commit to pricing strategies that react to price changes by competitors.”).

Predatory pricing skeptics would argue that the commitment to employ an aggressive pricing algorithm is itself not credible. The executives who implemented the algorithm could, in theory, abandon algorithmic pricing, or override it in some way.¹⁸⁵ The commitment problem shifts from credibility regarding a promise to charge below-cost prices to the credibility of a promise to use the pricing algorithm.¹⁸⁶ As predators did in the pre-internet era, online sellers can make the threat to use predatory algorithms credible by simply using predatory pricing algorithms that price below cost.¹⁸⁷ Evidence suggests that some dominant firms are already using algorithms to engage in predatory pricing.¹⁸⁸ This alone demonstrates those firms' commitment and makes their predatory threats credible.¹⁸⁹

Firms can also use contracts to make their commitments to use algorithmic pricing convincing. Contracts that limit the flexibility of a firm's decisionmakers to abandon a predatory pricing strategy make threats credible.¹⁹⁰ Firms already use contracts to make retail aggression credible. For example, large firms, such as Staples, promote their 110% price-match guarantees, promising to refund consumers 110%

¹⁸⁵ In light of the concern that pricing algorithms will raise prices too much and anger customers, some scholars advocate that managers should be able to override pricing algorithms "when necessary." See Bertini & Koenigsberg, *supra* note 80, at 83 (suggesting that to effectively understand what pricing algorithms communicate to the customer, companies "must develop a proper use case and narrative for implementing algorithmic pricing, assign an owner to monitor pricing guardrails, and empower that owner to manage or override the automation when necessary").

¹⁸⁶ Of course, managers should be more willing to use predatory pricing algorithms because they can be confident that algorithmically targeted below-cost pricing will lower the losses during the predation phase.

¹⁸⁷ See Brown & MacKay, *supra* note 80, at 14 ("To the extent that these algorithms are updated at lower frequency than prices are adjusted, this implies a short-run commitment to an automated pricing strategy.").

¹⁸⁸ See Riley Scott, *Network Gridlock: An Analysis of Competition Regulation in the Ridesharing Economy*, 26 N.Z. Bus. L.Q. 83, 106 (2020) ("Uber's opaque algorithmic pricing model is arguably the most pervasive source of its ability to engage in predatory pricing."); see also Matthew T. Wansley & Samuel N. Weinstein, *Venture Predation*, 48 J. CORP. L. (forthcoming 2023) (manuscript at 4–5) (on file with author) (describing how Uber engaged in predatory pricing). Any Amazon threat to engage in algorithmic predatory pricing would be credible because it has apparently used below-cost pricing to dominate online markets. Khan, *supra* note 138, at 774 ("As its history with Quidsi shows, Amazon's willingness to sustain losses has allowed it to engage in below-cost pricing in order to establish dominance as an online retailer.").

¹⁸⁹ See Brown & MacKay, *supra* note 80, at 1 ("Firms with faster pricing technology quickly respond to price changes by slower rivals, indicating commitment to automated strategies that depend on rivals' prices.").

¹⁹⁰ Kevin E. Davis, *The Demand for Immutable Contracts: Another Look at the Law and Economics of Contract Modifications*, 81 N.Y.U. L. REV. 487, 503–04 (2006) ("Anti-modification devices might also serve a second but related anticompetitive purpose: They might be used to enhance the credibility of threats to engage in predatory pricing.").

of the difference if another supplier charges a lower price.¹⁹¹ When a rival is charging a price equal to cost, this contractual obligation compels the seller with such a guarantee to charge a below-cost price.¹⁹² Firms committed to algorithmic predation could pursue a similar strategy. If needed, predators could enter into enforceable contracts to use a pricing algorithm instructed to maximize market share—losses be damned.¹⁹³

Finally, some theorists argue that commitments to pursue predatory pricing are not credible because shareholders will not tolerate losses.¹⁹⁴ As an initial matter, algorithmic predatory pricing can significantly reduce these losses by targeting the price cuts. Moreover, this argument rings hollow today as both firms and investors in the internet era are willing to fund sustained deficits in pursuit of long-term market power. Amazon is a case in point. Amazon famously bled money in its early days, absorbing losses for several years,¹⁹⁵ including losing billions of dollars by funding its Prime membership program and benefits.¹⁹⁶ Amazon's losses were not an unanticipated misstep, but part of a calculated long-term strategy that accepted present losses as the price for market dominance in the future.¹⁹⁷ Far from scaring investors off, shareholders bid up the price of Amazon stock. The more money that Amazon hemorrhaged, the more money that investors poured in.¹⁹⁸ Investors stayed loyal to Amazon even when its

¹⁹¹ *110% Price Match Guarantee*, STAPLES, <https://www.staples.com/sbd/cre/marketing/pmg/index.html> [<https://perma.cc/6GQM-N8MF>].

¹⁹² This assumes the firms are equally efficient and therefore have equal costs.

¹⁹³ *Cf.* Davis, *supra* note 190, at 503 (“Firms may attempt to make threats to engage in unprofitable predatory pricing credible by signing contracts that delegate responsibility for pricing decisions to managers who, either because of natural inclinations or incentive pay schemes, are more interested in eliminating competition than in maximizing firm profits.”).

¹⁹⁴ *See* Sappington & Sidak, *supra* note 51, at 276 (describing one scholar’s hypothesis that predatory pricing commitments are only credible when shareholders cannot remove managers during predation period (referencing John R. Lott, Jr., *ARE PREDATORY COMMITMENTS CREDIBLE?: WHO SHOULD THE COURTS BELIEVE?* 19 (1999))).

¹⁹⁵ Khan, *supra* note 138, at 712 (“Entering its sixth year in 2000, the company had yet to crack a profit and was mounting millions of dollars in continuous losses, each quarter’s larger than the last.”).

¹⁹⁶ *Id.* at 751 (“One Amazon expert tallies that Amazon has been losing \$1 billion to \$2 billion a year on Prime memberships.” (citing Deepa Seetharaman & Nathan Layne, *Free Delivery Creates Holiday Boon for U.S. Consumers at High Cost*, REUTERS (Jan. 2, 2015, 8:09 AM), <https://www.reuters.com/article/us-retail-shipping-holidays-analysis-idUSKBN0KB0P720150102> [<https://perma.cc/PZC2-8VM4>])).

¹⁹⁷ *Cf. id.* at 747 (“But for the vast majority of its twenty years in business, losses—not profits—were the norm [for Amazon].”).

¹⁹⁸ *Id.* at 748 (“Just as striking as Amazon’s lack of interest in generating profit has been investors’ willingness to back the company. . . . On a regular basis, Amazon would report losses, and its share price would soar.”).

earnings did not justify its stock price.¹⁹⁹ Their patience and investment eventually paid off.²⁰⁰ The Amazon experience illustrates that the fear of shareholder revolt does not render predatory pricing commitments incredible.²⁰¹ Although Amazon is perhaps the most noteworthy example, it is not unique.²⁰² Many investors take a long-term view, recognizing that short-term losses are a reasonable price for subsequent monopoly profits.²⁰³ Indeed, most business strategies entail short-term losses.²⁰⁴ In brief, risk-seeking shareholders will tolerate and even reward losses en route to market power.²⁰⁵

Ultimately, algorithms can help solve the commitment problem. Firms can magnify the deterrent value of predatory algorithms—just as they did in the pre-algorithm days—by actually using an algorithm that charges below-cost prices. Once rivals realize that the dominant firm has relinquished pricing decisions to an aggressive algorithm, they are more likely to exit the market.

3. *Recoupment by Algorithm*

The imposition and misinterpretation of the recoupment requirement in predatory pricing law has transformed and undermined anti-trust doctrine.²⁰⁶ Theorists argue that recoupment is not feasible because losses from predation will be too great to recover and previously defeated rivals will inevitably reenter the market once the predator raises prices during the recoupment phase.²⁰⁷ Both of these assumptions are deeply flawed. First, as explained previously, by using

¹⁹⁹ See *id.* at 713 (“Despite the company’s history of thin returns, investors have zealously backed it: Amazon’s shares trade at over 900 times diluted earnings, making it the most expensive stock in the Standard & Poor’s 500.”).

²⁰⁰ *Id.* at 712 (noting that after years of losses, “nobody seriously doubts that Amazon is anything but the titan of twenty-first century commerce”).

²⁰¹ See Marc J. Veilleux, Jr., “*Alexa, Can You Buy Whole Foods?*” *An Analysis of the Intersection of Antitrust Enforcement and Big Data in the Amazon-Whole Foods Merger*, 37 CARDOZO ARTS & ENT. L.J. 481, 508 (2019) (“[T]he presence of a company as large and powerful as Amazon makes recoupment moot if investors are willing to back this kind of business strategy.”).

²⁰² *E.g.*, Khan, *supra* note 138, at 786 (“The idea that investors are willing to fund predatory growth in winner-take-all markets also holds in the case of Uber.”).

²⁰³ *Id.* at 787 (“One might dismiss this phenomenon as irrational investor exuberance. But another way to read it is at face value: the reason investors value Amazon and Uber so highly is because they believe these platforms will, eventually, generate huge returns.”).

²⁰⁴ See Leslie, *supra* note 40, at 274–80 (discussing how firms often take actions which, though unprofitable, may still be rational, such as risk taking and limiting informational costs).

²⁰⁵ Khan, *supra* note 138, at 786 (“Recognizing that enduring early losses while aggressively expanding can lock up a monopoly, investors seem willing to back this strategy.”).

²⁰⁶ See generally Leslie, *supra* note 32 (critiquing the recoupment requirement).

²⁰⁷ See *supra* notes 52–56 and accompanying text.

targeted price cuts during the predation phase, the predator can minimize the losses, which makes recoupment easier.²⁰⁸

Second, this assertion of inevitable market reentry is empirically wrong. Standard Oil demonstrated how threats of future price predation can deter reentry by vanquished rivals.²⁰⁹ As the U.S. Bureau of Corporations recognized in the early twentieth century, “[f]or the independent [oil refiner] to attempt to establish himself in another town or section merely because prices are high there would involve additional expense, only to invite another disastrous conflict.”²¹⁰ This ever-looming threat of another round of below-cost pricing allows predators to charge supracompetitive prices without inviting new entry into the market.²¹¹ The firms that Standard Oil drove from the market did not reenter after the monopolist raised its prices.²¹² More recently, when major airlines employed predatory pricing strategies to successfully drive discount airlines from the market, those grounded airlines did not once again take flight when the dominant air carriers dramatically raised prices back up again.²¹³ In short, before the internet and AI, dominant firms that drove their rivals from the market with predatory pricing deterred re-entry by signaling that such intransigence would be greeted with another round of below-cost pricing, making reentry unlikely, not inevitable.

The theoretical arguments asserting the implausibility of recoupment were suspect when made, but algorithmic pricing undermines them even further. Algorithmic predation makes threats against reentry more credible and easier to implement. The algorithm can automatically respond to detected reentry by plummeting prices back

²⁰⁸ See *supra* Section II.B.1. See also Cheng & Nowag, *supra* note 128, at 63 (“[A]lgorithmic targeting may allow the dominant firm to maximize its post-predation recovery while minimizing the risks of market entry, which could undermine successful recoupment.”).

²⁰⁹ Leslie, *supra* note 21, at 590 (“Standard successfully signaled its rivals that if they reentered the market in response to Standard’s post-predation monopoly pricing, Standard would slash prices again until the entrant was driven from the market at a loss.”).

²¹⁰ U.S. BUREAU OF CORPORATIONS, *supra* note 23, at 668.

²¹¹ Leslie, *supra* note 21, at 590–91 (“Because Standard could easily render re-entry unprofitable, Standard could simultaneously charge a monopoly price while deterring re-entry.”).

²¹² *E.g.*, Dalton & Esposito, *supra* note 58, at 170 (“Standard successfully signaled Red C that immediate re-entry was not a feasible strategy.”); see also Leslie, *supra* note 21, at 590 (“Standard’s history, by contrast, shows examples of successful predation followed by no re-entry.”).

²¹³ *E.g.*, Paul Stephen Dempsey, *Predatory Practices & Monopolization in the Airline Industry: A Case Study of Minneapolis/St. Paul*, 29 *TRANSP. L.J.* 129, 159–60 (2002) (discussing how Northwest and Continental drove Kiwi International Airlines and Access Air out of business in the late 1990s by price-matching, then raising their prices once the airlines exited the market).

to their predatory level. Knowing this, no rational rival would continue to pay its fixed costs—as Bork and McGee predicted without evidence²¹⁴—and wait to reenter the market. Ultimately, algorithmic pricing can deter entry and reentry if the would-be entrant fears that the algorithm will respond to entry by again slashing prices to unprofitable levels.²¹⁵

Algorithmic pricing can enhance a firm’s reputation for pricing aggression. Scholars have long recognized that reputation can act as an independent “barrier to entry, allowing the predator to increase prices in the recoupment market.”²¹⁶ Algorithmic pricing can enhance reputation as a barrier to entry by making the below-cost pricing a relatively automatic response to entry.²¹⁷ When confronted with a dominant firm that uses predatory pricing algorithms, a potential entrant will be less sanguine that the dominant firm will reverse course and raise prices because an algorithm is less likely to retreat in a price war.

By maximizing reputational effects, algorithmic predation can inhibit market entry by deterring creditors from financing challengers to price predators. A dominant firm may flaunt its predatory algorithm as a warning sign to both competitors and their lenders.²¹⁸ The latter are unlikely to invest in firms that are targeted by a price predator or seek to enter a market dominated by a predatory monopolist.²¹⁹ Lenders are not eager to subsidize the fixed costs of an idle factory to play a waiting game that the lingering firm is likely to lose. Rational bankers and venture capitalists have little interest in funding the war chest of a firm in a battle whose outcome is uncertain or

²¹⁴ See *supra* notes 52–56 and accompanying text.

²¹⁵ Leslie, *supra* note 32, at 1716 (“[A] dominant firm could charge a monopoly price without inviting entry if potential entrants believed that the price would fall upon their entry.”).

²¹⁶ Bolton et al., *supra* note 37, at 2301.

²¹⁷ See *supra* notes 176–79 and accompanying text.

²¹⁸ Cf. Patrick Bolton, Joseph F. Brodley & Michael H. Riordan, *Predatory Pricing: Response to Critique and Further Elaboration*, 89 GEO. L.J. 2495, 2509 (2001) (discussing a non-algorithmic example).

²¹⁹ See NICOLA GIOCOLI, PREDATORY PRICING IN ANTITRUST LAW AND ECONOMICS: A HISTORICAL PERSPECTIVE 23 (2014) (“[I]t is undeniable that a (usually) small firm subjected to a predatory attack by a (supposedly) big market leader is not exactly the kind of business real-world lenders would rush to finance.”); Peter C. Carstensen, *Predatory Pricing in the Courts: Reflection on Two Decisions*, 61 NOTRE DAME L. REV. 928, 966 (1986) (noting that the risk of exclusion causes venture capitalists and entrepreneurs to be hesitant to enter the market); see also Wansley & Weinstein, *supra* note 188 (manuscript at 47) (“The theory of financial market predation suggests that the prey might not be able to acquire financing to wait out a price war because it cannot convince potential lenders that the predator’s advantage comes from below-cost pricing rather than lower costs or a higher quality product.”).

bleak.²²⁰ At a minimum, the rational lender will charge a premium,²²¹ which will make the target a less efficient competitor.²²² All of this makes recoupment more probable and predatory threats more credible.²²³

Beyond simply making threats of future price predation more credible, pricing algorithms can facilitate recoupment in novel ways unavailable to Standard Oil and the price predators of the past. Algorithms can magnify existing barriers to entry and create new ones, while still generating highly profitable sales that expedite recoupment. The remainder of this Section considers several aspects of algorithmic pricing that make recoupment even more likely: data manipulation, algorithmic restocking, timing issues, network effects, and consumer loyalty and sunk costs.

a. Big Data as a Barrier to Entry

Predatory firms that control large datasets can more easily recoup their losses from below-cost pricing. Large digital platforms can acquire valuable consumer data, even for consumers purchasing from other sellers.²²⁴ As noted previously, access to consumer data facilitates both targeted predatory pricing and traditional price discrimination, in which a seller can charge supracompetitive prices to

²²⁰ James A. Dalton & Louis Esposito, *Standard Oil and Predatory Pricing: Myth Paralleling Fact*, 38 REV. INDUS. ORG. 245, 251 (2011) (“Uncertainty about the costs of the potential entrant relative to the dominant firm as well as uncertainty about the incumbent firm’s reaction to entry diminishes the resolve of the potential entrant, as well as the willingness of the capital markets to supply funds.”); Joseph F. Brodley & George A. Hay, *Predatory Pricing: Competing Economic Theories and the Evolution of Legal Standards*, 66 CORNELL L. REV. 738, 746 n.15 (1981) (“Financers do not know with certainty if the new entrant will progress down the textbook curve that illustrates declining costs as cumulative output increases. Thus, they may balk at underwriting large short run losses.”).

²²¹ See JOHN E. KWOKA, JR. & LAWRENCE J. WHITE, *The Economic and Legal Context*, in *THE ANTITRUST REVOLUTION: ECONOMICS, COMPETITION, AND POLICY* 172, 181 (John E. Kwoka, Jr. & Lawrence J. White eds., 4th ed. 2004) (“[D]ifferential access arises when small firms have to pay a premium to borrow funds . . . because lenders favor the prospects of the leading firm . . .”).

²²² See, e.g., Jonathan B. Baker, *Predatory Pricing After Brooke Group: An Economic Perspective*, 62 ANTITRUST L.J. 585, 597 (1994) (discussing how Brown & Williamson believed it could take advantage of Liggett’s limited access to financing in *Brooke Group*).

²²³ See *id.* at 591 n.27 (arguing predatory pricing is more likely to succeed when rivals lack access to capital).

²²⁴ See Gal, *supra* note 7, at 82 n.75 (“[L]arge digital platforms that connect consumers and suppliers may provide the platform owner with advantages in data collection . . .”); Khan, *supra* note 138, at 780 (“Since Amazon commands a large share of e-commerce traffic, many smaller merchants find it necessary to use its site to draw buyers.”); STUCKE & GRUNES, *supra* note 127.

consumers with a high WTP.²²⁵ Howard Shelanski has explained, “[w]hen customer information is a useful input for a platform and is not equally available to that platform’s competitors, the informational advantage can help to entrench market power.”²²⁶ Control over big data is a significant barrier to entry.²²⁷ Armed with a unique and valuable dataset, a dominant firm that uses predatory pricing algorithms to acquire its monopoly position is better able to recoup through monopoly pricing (for at least some consumers) without losing sales to (less informed) rivals. In essence, the firm with dominion over big data is well-positioned to perform both steps of a predatory pricing strategy: predation and recoupment.

Even though internet shopping often is significantly easier than driving from store to store, search costs still exist as product offerings and options on websites can be complex and everchanging.²²⁸ Some large firms can use algorithms to increase consumers’ search costs. For example, Amazon can inhibit price comparisons by manipulating which items to highlight and which to burden by placing them several clicks away from consumers’ eyes. These search costs lead rational consumers to decline to invest their time and energy into chasing lower prices on the internet, and instead lead them to stick with the dominant firm.²²⁹ Professor Pascale Chapdelaine has explained how “large retailer platforms . . . exhibit market power due to the promise

²²⁵ EZRACHI & STUCKE, *supra* note 5, at 90 (“Some online retailers are tracking a consumer’s location, purchasing behavior, and other personal data to charge consumers with fewer options a higher price.”).

²²⁶ Howard A. Shelanski, *Information, Innovation, and Competition Policy for the Internet*, 161 U. PA. L. REV. 1663, 1680–81 (2013); *see also* Gal, *supra* note 7, at 81–82 (“[When] the algorithm’s special qualities or the unique dataset on which it operates cannot be copied or easily reconstructed (e.g., Google’s database), the algorithm (or the data used in it) may create a significant comparative advantage.”).

²²⁷ Daniel L. Rubinfeld & Michal S. Gal, *Access Barriers to Big Data*, 59 ARIZ. L. REV. 339, 373 (2017) (“[T]here are likely to be strong economic incentives to maintain control over large data sets and to create structural barriers, potentially rendering at least parts of the [data value] chain noncompetitive.”); Khan, *supra* note 138, at 785 (“A platform’s control over data, meanwhile, can also entrench its position. Access to consumer data enables platforms to better tailor services and gauge demand.” (citing Asher Schechter & Guy Rolnik, *Is the Digital Economy Much Less Competitive than We Think It Is?*, PROMARKET (Sept. 23, 2016), <https://promarket.org/digital-economy-much-less-competitive-think> [<https://perma.cc/H5YR-7WAX>])).

²²⁸ *See* Rory Van Loo, *Helping Buyers Beware: The Need for Supervision of Big Retail*, 163 U. PA. L. REV. 1311, 1329 (2015) (“[S]earching for products online brings complexity and time-consuming comparisons of its own, producing thousands of search results for a single product in a single online retailer.”).

²²⁹ *See* EZRACHI & STUCKE, *supra* note 5, at 108–09; Chapdelaine, *supra* note 115, at 6–7 (“As Ezrachi & Stucke explain, more complex product offerings require more investment in time for buyers (or ‘search costs’), making consumers less inclined to look for prices elsewhere; such exercise of comparison might be futile as measuring one complex offering against others may be harder to decipher.”).

of efficiency through reduced search costs, a developed relationship of trust between consumers and suppliers about competitive prices, and the comfort and convenience of an established account, which may take precedence over the vigilance required and expected of shoppers.”²³⁰ While dominant platforms may seemingly reduce search costs by keeping consumers fixated on one particular platform, they can increase search costs within the platform in ways that make it harder for consumers to purchase from rivals.²³¹

Savvy predators can use their data resources to influence consumer purchasing decisions and to manipulate consumer preferences.²³² The strategy of targeted advertising and coupons used during the predation phase can be reconfigured during the recoupment phase as “businesses use microtargeted ads to shape consumers’ preferences and steer them into a particular consumption pattern, effectively locking them into a lifestyle determined by their past choices and those of likeminded consumers.”²³³ Properly executed, this strategy can keep consumers locked into the monopolist,²³⁴ thus making entry or reentry into the market harder for other firms.

Importantly, a predatory firm can continue the price discrimination strategy of the predation phase during the recoupment phase. After the predator acquires monopoly power, its pricing algorithm can persist in monitoring the WTP of individual consumers and adjusting their personalized prices, charging monopoly prices to entrenched customers and lower prices to customers at risk of switching.²³⁵ For all

²³⁰ Chapdelaine, *supra* note 115, at 17.

²³¹ See Miller, *supra* note 113, at 80 (“Marketing techniques that create and exploit consumers’ high search costs undermine the ability to compare prices and can lower overall welfare and harm consumers. They can also be very annoying and frustrating.”).

²³² See TUROW, *supra* note 73, at 92 (“The cookie was the most crucial of a range of emerging developments that deepened the notion that the Web was a place for promoting products as well as collecting data on individuals and then using that information to entice them to make a purchase.”); Chapdelaine, *supra* note 115, at 21 (“[T]he power to significantly influence consumers’ decisions through the use of their personal data skews asymmetries between buyer and seller in favor of the latter even more than has ever been the case.”); Jerry Useem, *How Online Shopping Makes Suckers of Us All*, THE ATLANTIC, May 2017, at 62, 67 (“The software identifies the goods that loom largest in consumers’ perception and keeps their prices carefully in line with competitors’ prices, if not lower. The price of everything else is allowed to drift upward.”).

²³³ Wagner & Eidenmüller, *supra* note 117, at 583–84.

²³⁴ See *id.* at 584 (“[S]haping consumers’ preferences by microtargeted ads prevents consumers from experimenting . . .”).

²³⁵ See Competition & Mkts. Auth., *Algorithms: How They Can Reduce Competition and Harm Consumers*, GOV.UK (Jan. 19, 2021), <https://www.gov.uk/government/publications/algorithms-how-they-can-reduce-competition-and-harm-consumers/algorithms-how-they-can-reduce-competition-and-harm-consumers> [https://perma.cc/R36F-2NGE] (“Firms can also use machine learning and data science techniques to reduce customer attrition (or ‘churn’), by analysing what characteristics or behaviours of their

these reasons, pricing algorithms can harness big data to facilitate recoupment.

b. Recoupment Through Automated Restocking

Long before internet shopping existed, price predators would sometimes recoup their losses by charging supracompetitive prices for replacement products. For example, Champion Spark Plug Co. monopolized the market for spark plugs by charging below-cost prices for the first set of spark plugs in a car—known as original equipment or “OE” plugs—knowing that “[b]y custom and practice among mechanics, the aftermarket plug is usually the same brand as the OE plug.”²³⁶ In other words, by taking a loss on the OE plugs, Champion could lock in subsequent sales of monopoly-priced replacement plugs because mechanics consistently replaced spark plugs with the same brand. Consequently, Champion could be confident of recouping its early losses with a string of monopoly profits.²³⁷

AI-assisted purchasing software represents the internet version of replacement spark plugs. With the advent of the Internet of Things, many consumers use shopping bots that automatically order consumable products.²³⁸ For example, washing machines spontaneously purchase detergent when supplies are low, and refrigerators monitor their own contents and order items for restocking based on previous purchases.²³⁹ This can create a lock-in effect for both brand and supplier. Similarly, digital personal assistants (DPAs) can use algorithms to replenish home supplies, “spar[ing] the consumer the agony of choice by taking past choices as a blueprint for current preferences.”²⁴⁰ The use of DPAs reduces consumers’ price sensitivity because consumers do not see comparative prices, and thus suppliers are better able to price discriminate.²⁴¹ For platforms that facilitate consumers receiving automatic shipments of consumable products—

customers are predictive of exit or switching. These churn models may then inform firms’ decisions about whether and how much to increase prices” (citation omitted)).

²³⁶ *Ford Motor Co. v. United States*, 405 U.S. 562, 565 (1972) (emphasis omitted).

²³⁷ See JOEL B. DIRLAM & ALFRED E. KAHN, *FAIR COMPETITION: THE LAW AND ECONOMICS OF ANTITRUST POLICY* 217 (1954) (discussing below-cost pricing in spark plugs).

²³⁸ See EZRACHI & STUCKE, *supra* note 5, at 19 (“[T]he Internet of Things would widen the scope of data for the algorithms. As more products have sensors, the interfaces will include anything from household appliances, clothing, cars, and bicycles, to streetlights, airports, smart building materials, and human-embedded sensors.”).

²³⁹ See Wagner & Eidenmüller, *supra* note 117, at 600 (“The Internet of Things and the shopping bots coming with it will add another layer of consumer lock-in.”).

²⁴⁰ *Id.* at 599.

²⁴¹ See EZRACHI & STUCKE, *supra* note 5, at 194–96 (discussing the process by which DPAs facilitate lock-in and enable more effective price discrimination).

whether food, office supplies, or cleaning products—the automation may give the dominant seller a functional lock on replacement products. This increases both the likelihood and rate of recoupment.

c. The Time Needed to Recoup

Federal courts have held that the recoupment requirement is not satisfied when the period for recoupment is protracted. For example, in *Matsushita Electric Industrial Co. v. Zenith Radio Corp.*²⁴² the Supreme Court asserted that the alleged predatory pricing conspiracy was implausible because the recoupment would take too long.²⁴³ The Fifth Circuit similarly affirmed summary judgment for a predatory pricing defendant because the plaintiff could not prove that the defendant “would be able to control prices for any meaningful period, because other competitors easily c[ould] enter the market.”²⁴⁴ Although the court never defined what constitutes a “meaningful period,” Supreme Court precedent implies that this is the length of time required to recoup losses incurred during the predation phase of a predatory pricing strategy.²⁴⁵

Algorithmic predation could condense the time horizon for recoupment in several ways. First, by targeting the predatory price cuts, pricing algorithms minimize losses during the predation phase.²⁴⁶ By reducing the magnitude of losses suffered by the predator, algorithmic pricing reduces the period of time necessary to recoup those losses. This makes recoupment more likely.

Second, and related, algorithmic pricing hastens recoupment by facilitating price discrimination from the outset. As traditionally described, predatory pricing has two distinct periods: the predation phase (with below-cost pricing) and the recoupment phase (with monopoly pricing). Algorithmic pricing can blur these two phases by

²⁴² 475 U.S. 574 (1986).

²⁴³ *See id.* at 592–93 (“If the losses have been substantial—as would likely be necessary in order to drive out the competition—petitioners would most likely have to sustain their cartel for years simply to break even.”). The *Matsushita* Court misanalysed the issue by incorrectly assuming the recoupment phase must be at least as long as the predation phase. *See Leslie, supra* note 29, at 1561 & n.189 (“[T]he majority miscalculated how recoupment for twenty years of below-cost pricing could occur in short order.”).

²⁴⁴ *C.A.T. Indus. Disposal, Inc. v. Browning-Ferris Indus., Inc.*, 884 F.2d 209, 211 (5th Cir. 1989) (per curiam).

²⁴⁵ The Supreme Court in *Brooke Group* quoted *Matsushita* to reiterate that “[i]n order to recoup their losses, [predators] must obtain enough market power to set higher than competitive prices, and then must sustain those prices long enough to earn in excess profits what they earlier gave up in below-cost prices.” *Brooke Grp. Ltd. v. Brown & Williamson Tobacco Corp.*, 509 U.S. 209, 225–26 (alterations in original) (quoting *Matsushita*, 475 U.S. at 590–91).

²⁴⁶ *See supra* Section II.B.1.a.

allowing the predator to charge below-cost prices to some consumers (predating) while charging monopoly prices to other consumers (recouping). Because AI allows firms to identify those consumers with relatively high reservation prices (WTP) and charge them supracompetitive prices,²⁴⁷ the algorithmic predator can price discriminate during the predation period and use the profits from above-cost sales to subsidize the losses on below-cost sales in real time. Instantaneous cross-subsidization reduces losses during predation, and thus makes recovering these losses easier during the recoupment phase.²⁴⁸

Third, in addition to altering the dynamics of the predation phase, algorithmic pricing can accelerate recoupment after the predator's rivals have exited the market. Unlike the traditional model of predatory pricing in which the monopolist charges one standard price to all consumers during the recoupment phase, pricing algorithms allow the monopolist to continue price discriminating. This may permit the monopolist to charge even more than the monopoly price to consumers with the highest WTP.²⁴⁹ Moreover, because pricing algorithms operate so swiftly,²⁵⁰ sellers can press their advantage further by expeditiously targeting consumers with a higher WTP.

All these features of algorithmic pricing condense the time required for recoupment, thus making complete recovery before competitors reenter more likely.

d. Network Effects

In some markets, predators may rely on network effects to ensure the recoupment of their losses suffered during the predation phase. In a market that exhibits network effects, a dominant firm can become entrenched once it has the lion's share of the market.²⁵¹ For example,

²⁴⁷ See *supra* Section II.B.1.b.; Chapdelaine, *supra* note 115, at 11 (discussing how online sellers can “draw[] distinctions about price sensitivity between the ‘lazy’ fidelity consumer who does not shop around and the active shopper navigating back and forth between websites”).

²⁴⁸ This narrower time frame also increases the credibility of the predatory threat. See Leslie, *supra* note 32, at 1731 (“This ability to fund predation from another market’s profits in turn gives the predator visible staying power, which increases the credibility of its predatory threat.”); see also DIRLAM & KAHN, *supra* note 237, at 142 (discussing the strategic advantage of staying power).

²⁴⁹ See JACK HIRSHLEIFER, PRICE THEORY AND APPLICATIONS 260 (3d ed. 1984) (describing how perfect price discrimination would enable a firm to charge consumers “according to an individually tailored price schedule”).

²⁵⁰ Gal, *supra* note 7, at 84 (“The speed and sophistication of algorithms, combined with the increased availability of real-time data and faster connectivity, enable them to quickly recognize changes in market conditions and to autonomously change their decisional parameters accordingly.”).

²⁵¹ See Khan, *supra* note 138, at 785 (“Since popularity compounds and is reinforcing, markets with network effects often tip towards oligopoly or monopoly.”).

Microsoft maintained its monopoly over operating systems, in part, because consumers wanted to use the operating system that had the most applications, and application developers wanted to write applications for the operating system used by the most consumers.²⁵² When Microsoft feared that the evolution of Netscape's browser would undermine this network effect—because application developers could write programs for browsers, instead of operating systems—Microsoft gave away its browser for free. This was akin to predatory pricing because Microsoft suffered a marginal loss for each browser it distributed,²⁵³ but Microsoft knew that it would recoup this loss in the browser market through monopoly pricing for its operating systems.²⁵⁴

Understanding this dynamic, a rational firm may use predatory algorithms to secure control over a market characterized by network effects, confident that recoupment is likely.²⁵⁵ For example, Uber allegedly used algorithmic predatory pricing to monopolize the ridesharing market with the expectation that it would recoup its losses after it monopolized a market that was protected by the network-effects barrier to entry.²⁵⁶ The district court in *SC Innovations, Inc. v. Uber Technologies, Inc.* recognized how network effects create a barrier to entry that “provides a plausible means for Uber to recoup its losses from alleged predatory pricing.”²⁵⁷ Because network effects facilitate recoupment, firms should be more willing to engage in

²⁵² *United States v. Microsoft Corp.*, 253 F.3d 34, 55 (D.C. Cir. 2001) (per curiam) (“[M]ost consumers prefer operating systems for which a large number of applications have already been written; and . . . most developers prefer to write for operating systems that already have a substantial consumer base.”).

²⁵³ See Daniel L. Rubinfeld, *Maintenance of Monopoly: U.S. v. Microsoft (2001)* (“[Microsoft] was giving away something . . . that it had spent a lot of money to develop and distribute . . . for which the leading competitor was charging. It was only when Microsoft's gains from preserving and extending its monopoly (recoupment) were included that Microsoft's conduct appeared to be profitable.”), in *THE ANTITRUST REVOLUTION: ECONOMICS, COMPETITION, AND POLICY* 476, 489–90 (John E. Kwoka, Jr. & Lawrence J. White eds., 4th ed. 2004).

²⁵⁴ See Leslie, *supra* note 32, at 1722 (“Microsoft had no intention of earning profits in the browser market. Microsoft's goal was to stop Netscape from encroaching upon the operating systems market.”).

²⁵⁵ See Mark A. Lemley & David McGowan, *Could Java Change Everything? The Competitive Propriety of a Proprietary Standard*, 43 *ANTITRUST BULL.* 715, 725 (1998) (noting investments in predation are more likely to be recouped in a market with network effects).

²⁵⁶ See Scott, *supra* note 188, at 91 (discussing a Sherman Act claim “alleg[ing] that Uber set prices commuters were charged below cost in order to gain a strangle-hold on the market in leveraging structural features of the market, namely barriers to entry in the form of network effects”).

²⁵⁷ No. 18-cv-07440, 2020 WL 2097611, at *10 (N.D. Cal. May 1, 2020).

algorithmic predation in such markets.²⁵⁸ Moreover, network effects may be more common in online environments characterized by consumer loyalty or lock-in.²⁵⁹

e. Customer Loyalty

Recoupment for predatory pricing is more likely if consumers are sufficiently loyal to the firm that charged them a below-cost price. Loyalty may lead consumers to continue to purchase from that seller after the price increases. Ironically, perhaps, pricing algorithms charge loyal customers higher prices.²⁶⁰ Dominant online firms can use AI to generate customer loyalty.²⁶¹ For example, they can use consumers' AI-collected personal data to profile consumers and tailor online experiences and prices in ways that keep consumers hooked on that particular platform.²⁶² Engendering loyalty by keeping customers satisfied is, of course, neither anticompetitive nor illegal.²⁶³ But this loyalty makes recoupment more feasible and, thus, by the Supreme

²⁵⁸ See Wansley & Weinstein, *supra* note 188 (manuscript at 48) (“Venture predators will often target markets subject to network effects. . . . The predator and its financiers also count on these network effects to create a barrier to entry which will allow the predator to charge supracompetitive prices to recoup its losses. . . .”); Steven C. Salop & R. Craig Romaine, *Preserving Monopoly: Economic Analysis, Legal Standards, and Microsoft*, 7 GEO. MASON L. REV. 617, 639 (1999) (describing how network effects could make price predation profitable for Microsoft).

²⁵⁹ See STUCKE & GRUNES, *supra* note 127, at 162 (collecting sources noting the strength of network effects in online markets).

²⁶⁰ TUROW, *supra* note 73, at 22 (“While mainstream retailers continue to encourage shoppers to consider loyalty a reward, it is actually giving way to complex algorithms that often punish people for fidelity. . . . [One] company actually lowers prices for individuals deemed less loyal while keeping the prices higher for the ones identified as more loyal.”); Gautier et al., *supra* note 80, at 409–10 (noting instances of Amazon charging higher prices to repeat customers).

²⁶¹ See Wagner & Eidenmüller, *supra* note 117, at 582 (citing Laika Satish & Norazah Yusof, *A Review: Big Data Analytics for Enhanced Customer Experiences with Crowd Sourcing*, 116 *PROCEDIA COMPUT. SCI.* 274, 278 (2017)); Seshadri Tirunillai & Gerard Tellis, *Extracting Dimensions of Consumer Satisfaction with Quality from Online Chatter: Strategic Brand Analysis of Big Data Using Latent Dirichlet Allocation 3–4* (Mar. 13, 2014) (unpublished study), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2408855 [<https://perma.cc/V94Y-T7F3>] (noting studies suggesting that “big data analytics can help increase customer satisfaction and loyalty”); see also Khan, *supra* note 138, at 750 (“One of the primary ways Amazon has built a huge edge is through Amazon Prime, the company’s loyalty program, in which Amazon has invested aggressively.”).

²⁶² See Chapdelaine, *supra* note 115, at 10–11 (describing types and usage of data that firms collect); EZRACHI & STUCKE, *supra* note 5, at 94 (“[C]ompanies may seek passive consumers with low engagement who will continue paying high prices for poor service—and tailor an environment for them which is free from promotions and ensures continuing purchases.”).

²⁶³ See, e.g., *United States v. United Shoe Mach. Corp.*, 110 F. Supp. 295, 336, 352 (D. Mass. 1953) (dismissing some Sherman Act claims against defendant shoe machinery company absent evidence of a violation beyond “customer inertia”).

Court's calculus in *Brooke Group*, makes predatory pricing more likely and more dangerous.²⁶⁴

A dominant firm can use its scale and first-mover status to create a form of path dependence for consumers. For example, a majority of online shoppers start with Amazon's platform to search for products,²⁶⁵ giving the tech behemoth the power to manage and restrict what consumers see. In doing so, pricing algorithms can manipulate perceived switching costs,²⁶⁶ which the Supreme Court has recognized in non-algorithmic contexts can entrench monopoly power.²⁶⁷ Many consumers are dependent on—if not enamored with—a particular internet platform that controls their access to competitive price information.

Consumers want to minimize search and transactions costs, not just purchase price. When it is easier to purchase products from a single major source, consumers may rely on that source even when prices on some individual products are inflated. For example, many consumers simply purchase the relatively high-priced item from Amazon off their phone or home computer without bothering to visit a brick-and-mortar store or even other websites.²⁶⁸ The convenience of immediate purchases with quick delivery makes physical (or even comparison) shopping unnecessary for many consumers.

In some cases, consumer loyalty may reflect a mixture of lock-in and refusal to ignore sunk costs. Online sellers, such as Amazon, can

²⁶⁴ See *Brooke Grp. Ltd. v. Brown & Williamson Tobacco Corp.*, 509 U.S. 209, 226 (1993) (describing how market dynamics affect the likelihood of recoupment).

²⁶⁵ See *infra* note 269; see also Khan, *supra* note 138, at 714 (“Close to half of all online buyers go directly to Amazon first to search for products, and in 2016, the Reputation Institute named the firm the ‘most reputable company in America’ for the third year running.”).

²⁶⁶ See *id.* at 753 (“Although competition for online services may seem to be ‘just one click away,’ research drawing on behavioral tendencies shows that the ‘switching cost’ of changing web services can, in fact, be quite high.”).

²⁶⁷ See *Eastman Kodak Co. v. Image Tech. Servs., Inc.*, 504 U.S. 451, 476 (1992) (“If the cost of switching is high, consumers who already have purchased the equipment, and are thus ‘locked in,’ will tolerate some level of service-price increases before changing equipment brands.”).

²⁶⁸ Rory Van Loo, *Digital Market Perfection*, 117 MICH. L. REV. 815, 824 (2019) (“Millions of Americans shop online through Amazon despite the fact that they could save money by combing through other websites’ options or visiting stores in person.”); Cheng & Nowag, *supra* note 128, at 48 (noting study that found “that algorithmic sellers are more likely to be more successful and win the all-important ‘Buy Box’ on Amazon Marketplace even though they do not necessarily offer the lowest prices” (citing Le Chen, Alan Mislove & Christo Wilson, *An Empirical Analysis of Algorithmic Pricing on Amazon Marketplace*, in *PROCEEDINGS OF THE 25TH INTERNATIONAL CONFERENCE ON WORLD WIDE WEB* 1339, 1346 (Jacqueline Bourdeau et al. eds., 2016))); see also EZRACHI & STUCKE, *supra* note 5, at 114 (noting that some online customers are “sleepers” who simply purchase from the website they are accustomed to using).

encourage consumers to incur sunk costs by participating in programs like Amazon Prime. Once they pay their membership fee, many consumers feel the need to justify this upfront expense by maximizing their purchases from Amazon. Studies demonstrate that the sunk-cost effect leads Prime members to both start their online shopping at Amazon and to increase their overall purchases from Amazon.²⁶⁹ This is not merely a happy coincidence for Amazon; it created the Prime program—which initially operated at a significant loss²⁷⁰—in order to change consumers’ browsing and buying habits.²⁷¹ This has an exclusionary effect, as most Prime members do not even consider shopping at competitor sites.²⁷² The manipulation of sunk costs can help a dominant firm recoup its losses from algorithmic predatory pricing through consumer loyalty.

C. *The Battle of the Algorithms*

In theory, the intended victim of algorithmic predation could simply implement its own pricing algorithm that would counteract and thwart the predator’s algorithm. This is possible in some markets. If two large firms share a duopoly in which both firms possess large war

²⁶⁹ See Press Release, Feedvisor, Most U.S. Consumers Would Purchase on Amazon Before Other E-Commerce Sites, Feedvisor Study Finds (Mar. 19, 2019), <https://www.globenewswire.com/news-release/2019/03/19/1757273/0/en/Most-U-S-consumers-would-purchase-on-Amazon-before-other-e-commerce-sites-Feedvisor-study-finds.html> [<https://perma.cc/S9TQ-MLL6>] (“Three-fourths of consumers go to Amazon when they are ready to make a purchase.”); Spencer Soper, *More Than 50% of Shoppers Turn First to Amazon in Product Search*, BLOOMBERG (Sept. 27, 2016, 12:01 AM), <https://www.bloomberg.com/news/articles/2016-09-27/more-than-50-of-shoppers-turn-first-to-amazon-in-product-search> [<https://perma.cc/ZF53-K6H7>] (“Fifty-five percent of those surveyed go to Amazon first when searching for products”); Complaint ¶ 16, District of Columbia v. Amazon.com, Inc., No. 2021 CA 001775 B (D.C. Super. Ct. June 1, 2021) (“Sixty-six percent of consumers start their search for new products on Amazon, and a staggering 74% go directly to Amazon when they are ready to buy a specific product.”); Khan, *supra* note 138, at 752 (“Moreover, the annual fee drives customers to increase their Amazon purchases in order to maximize the return on their investment.”); *id.* at 751–52 (“According to analysts, customers increase their purchases from Amazon by about 150% after they become Prime members.”).

²⁷⁰ Khan, *supra* note 138, at 751 (“As with its other ventures, Amazon lost money on Prime to gain buy-in.”).

²⁷¹ See Brad Stone, *What’s in Amazon’s Box? Instant Gratification*, BLOOMBERG BUSINESSWEEK (Nov. 24, 2010, 5:00 PM), <https://www.bloomberg.com/news/articles/2010-11-24/whats-in-amazons-box-instant-gratification> [<https://perma.cc/T92L-Q2JP>] (quoting former Amazon employee and Prime team member Vijay Ravindran as saying: “It was never about the \$79. It was really about changing people’s mentality so they wouldn’t shop anywhere else.”).

²⁷² See Khan, *supra* note 138, at 752 (“One study found that less than 1% of Amazon Prime members are likely to consider competitor retail sites in the same shopping session.”); *id.* (“As a result, Amazon Prime users are both more likely to buy on its platform and less likely to shop elsewhere.”).

chests of money and have access to equally efficient pricing algorithms, then neither would likely prevail in a predatory price war.²⁷³ Anticipating a costly war followed by an unprofitable stalemate, predatory pricing is less likely in these markets. A duopoly or oligopoly may mimic the market dynamics of the pre-algorithmic age, in which dominant firms employed predatory pricing against smaller rivals. In short, some markets are more susceptible to predatory pricing than others; that remains true in the algorithmic era.

In the future, in some markets, price wars will be fought by algorithms.²⁷⁴ Although small firms could also purchase and employ pricing algorithms,²⁷⁵ this is not a perfect defense to algorithmic predation. As with traditional predatory pricing, the small firm targeted with predatory pricing must be willing to take losses—losses that it probably cannot recoup because (unlike the predator) it probably will not end up with monopoly power and the ability to set price for the market. Many firms targeted by predatory pricing algorithms will thus be unlikely to fight back effectively.

In the AI age, the battle for market supremacy will be fought with two weapons: algorithms and data. Both are necessary. Data without the means to analyze and apply it provides little value in the competitive combat zone. Conversely, an algorithm requires copious amounts of data to properly set and reset profit-maximizing prices continuously throughout the day. In any given market, the firm with the best combination of a superior algorithm and data to feed into it is more likely to win the competitive battle.²⁷⁶

Not all pricing algorithms are created equally. Superior algorithms can reactively change prices faster than rivals.²⁷⁷ Empirical research shows firms with “superior pricing technology” change their online prices consistently throughout the day while rival firms with inferior algorithms only change prices once a day or week.²⁷⁸ The

²⁷³ This could conceivably describe Uber and Lyft in the future.

²⁷⁴ See EZRACHI & STUCKE, *supra* note 5, at 14 (“Amazon’s algorithms will increasingly be pitted against other algorithms (rather than humans) for pricing decisions.”).

²⁷⁵ See MacKay & Weinstein, *supra* note 76, at 126 (“Third-party vendors sell pricing algorithms that even small firms can use to customize their pricing.”).

²⁷⁶ Experts have debated which is more important, the data or the algorithm. See STUCKE & GRUNES, *supra* note 259, at 127 (“Some argue that in some industries simple algorithms with lots of data will eventually outperform sophisticated algorithms with little data.”). Both are important in their own way.

²⁷⁷ See MacKay & Weinstein, *supra* note 76, at 146 (“Brown and MacKay also found evidence that the faster firms were more likely to change the price of a particular product after a slower retailer changed the price of that product.”).

²⁷⁸ See Brown & MacKay, *supra* note 80, at 3, 13–14 (describing the difference in frequency of price changes between retailers with faster pricing algorithms and retailers with slower ones).

fastest pricing algorithm is better able to learn, pivot, and outmaneuver its rivals.²⁷⁹ Firms with faster algorithms lower their prices more quickly and more frequently.²⁸⁰ Algorithms that respond to external changes and update prices more frequently are more expensive and may be out of the reach of smaller firms.²⁸¹ This algorithmic advantage allows these firms to consistently show lower prices to the buying public.²⁸²

Similar to how turn-of-the-century manufacturers competed for physical inputs, firms that employ algorithms compete for data inputs.²⁸³ While some commentators see data as cheap and easily available,²⁸⁴ the quantity and quality of data varies across companies.²⁸⁵ Dominant firms, such as large retailers, have significant data advantages over their smaller rivals.²⁸⁶ Retailers with both online and

²⁷⁹ See STUCKE & GRUNES, *supra* note 259, at 23–24 (“Finally value comes from velocity, namely being the first to collect, analyse, and use the data. With real-time monitoring and self-learning computer algorithms that automatically update their inferences and predictions, companies can out-manoeuvre rivals in being the first to decipher material changes in the market.”).

²⁸⁰ See MacKay & Weinstein, *supra* note 76, at 116 (“Typically, the firm with a faster algorithm will have a competitive advantage The slower firm can perceive the ability of the faster firm to quickly reduce prices as a threat, limiting its incentives to compete on price.”); Brown & MacKay, *supra* note 80, at 7 (“We show that firms differ in the frequency with which they change prices and that faster firms react to rivals’ price changes. We also find that faster firms have lower prices than slower firms.”); *id.* at 12 (“Stylized Fact 2: Retailers with the fastest pricing technology quickly react to price changes of slower rivals, consistent with the use of automated pricing algorithms.”).

²⁸¹ See Brown & MacKay, *supra* note 80, at 7 (“The frequency with which a firm can update prices depends on investments in pricing technology, which may differ across firms.”).

²⁸² See *id.* at 14 (“Stylized Fact 3: Firms with faster pricing technology have persistently lower prices for identical products.”); *id.* (“By using a high-frequency pricing algorithm, firms may commit to best-respond to their rivals. . . . [T]his best response is often to undercut rivals’ prices”).

²⁸³ See STUCKE & GRUNES, *supra* note 259, at 38 (“[C]ompanies, with data-driven business models, are increasingly undertaking strategies to obtain and sustain a competitive advantage. Companies strive to acquire a ‘big data-advantage’”); *id.* at 41 (“[D]ata, the OECD observed, can be a key competitive input”).

²⁸⁴ See *id.* at 42 (“To downplay the competitive significance of Big Data, some claim, without empirical support, that data ‘is ubiquitous, low cost, and widely available.’” (quoting Darren S. Tucker & Hill B. Wellford, *Big Mistakes Regarding Big Data*, ANTITRUST SOURCE, Dec. 2014, at 7)).

²⁸⁵ See *id.* (noting that companies invest significant money to secure data that is not publicly available).

²⁸⁶ See MacKay & Weinstein, *supra* note 76, at 126 (“Amazon’s pricing algorithm takes advantage of the company’s trove of customer and competitor data, incorporating customer preferences, rivals’ prices, product supply, and many other criteria in setting prices.”); TUROW, *supra* note 73, at 130 (“Giant retailers . . . had the means to compile an arsenal of data to profile their customers’ shopping habits These retailers typically collected personal information based on loyalty card (or app) registration or via credit (or debit) card identification customers provided at checkout.”).

physical outlets can combine their data to understand individual customers' preferences and price points.²⁸⁷

Dominant firms with the best combination of sophisticated pricing algorithms and valuable data are more likely to win a predatory pricing war, in part because they are better able to price discriminate.²⁸⁸ Professors Ariel Ezrachi and Maurice E. Stucke have explained:

As the competitive value of data increases, companies will strive to acquire a 'data advantage,' and thus a competitive advantage over rivals. Companies will increasingly invest in computer algorithms to analyze the volume and variety of data. Even for publicly available data, velocity will be critical—namely, getting and analyzing the data quickly to outmaneuver rivals.²⁸⁹

A firm with more and better data has a significant advantage in any algorithmic price war.²⁹⁰ Dominant firms tend to have more data and better data.²⁹¹ Google, for example, has superior data because it can scan the contents of Gmail as well as monitor the comings and goings of consumers who use Google-owned Nest technology.²⁹² Sophisticated pricing algorithms that can learn by doing can outwit and outflank less state-of-the-art algorithms.²⁹³ The learn-by-doing algorithm will become even more dominant as it receives and processes more data.²⁹⁴ In some markets, the dominant firm with a powerful algorithm can better harvest and analyze consumer data, which "can have a snowball effect, enabling a provider to better target customers, thereby reinforcing its power by attracting additional users."²⁹⁵ Rational firms with inferior pricing algorithms will appre-

²⁸⁷ See STUCKE & GRUNES, *supra* note 259, at 21 (discussing how Tesco in the United Kingdom collects and uses its shoppers' purchase and visiting history in both its stores and online).

²⁸⁸ See EZRACHI & STUCKE, *supra* note 5, at 238 ("Firms with more users, more personal data, and better algorithms can better price discriminate . . .").

²⁸⁹ *Id.* at 20–21 (citing Andrew McAfee and Erik Brynjolfsson, *Big Data: The Management Revolution*, HARV. BUS. REV., Oct. 2012, at 60).

²⁹⁰ *Id.* at 14 ("Data, and importantly, the scale of data, are key. . . . Having control over, and being able to quickly analyze, the personal data can provide the platform operator a key competitive advantage.").

²⁹¹ See, e.g., STUCKE & GRUNES, *supra* note 259, at 89 (discussing Google's acquisition of companies involved in the smart home industry in order to get better data on individual consumer behavior).

²⁹² *Id.* at 89, 188.

²⁹³ EZRACHI & STUCKE, *supra* note 5, at 14 ("As the industry-wide use of algorithms increases, the algorithms, through learning by doing, will better anticipate and respond to rival algorithms' actions.").

²⁹⁴ *Id.* at 16 ("The algorithms' capacity to learn increases as they process more relevant data.").

²⁹⁵ *Id.* at 238.

ciate their inability to compete as effectively on price²⁹⁶ and hence should be less likely to wage war against a predator. A swift surrender may be the most economical response.

Dominant firms with access to the most complete data and faster, more sophisticated algorithms can more easily both price predate and recoup their losses. In sum, they will win the battle of the pricing algorithms.

D. Summary

For decades, theorists have argued that predatory pricing is implausible because the predator will suffer asymmetric losses during the predation phase, the predator cannot make a credible commitment to predate, and the predator has no reasonable prospect of recoupment because rivals will reenter the market during the recoupment phase. The Supreme Court has consequently claimed that “it is plain that the obstacles to the successful execution of a strategy of [price] predation are manifold, and that the disincentives to engage in such a strategy are accordingly numerous.”²⁹⁷ The Court used such observations to make predatory pricing claims almost impossible to prove.

These theoretical arguments were always incorrect, but AI removes these alleged obstacles to successful price predation. First, pricing algorithms can target rivals’ customers for below-cost prices, thus eliminating the risk and magnitude of any asymmetric losses. Second, pricing algorithms can address the commitment canard, making the threat to charge below-cost prices more credible. And third, reliance on pricing algorithms can make recoupment more likely. In short, algorithmic pricing reduces the perceived disincentives for using predatory pricing to monopolize a market.

III

THE DOCTRINAL AND POLICY IMPLICATIONS OF ALGORITHMIC PREDATION

The evolution of pricing algorithms has important implications for antitrust law. Current doctrine is extremely deferential to the pricing policies of monopolists—grounded in the assumption that predatory pricing does not occur. That hypothesis was wrong at its genesis, when John McGee falsely claimed he had proven that

²⁹⁶ See MacKay & Weinstein, *supra* note 76, at 117 (“When firms with superior technology commit to this strategy, firms with inferior technology know that their rivals can be relied on to undercut their prices.”).

²⁹⁷ *Cargill, Inc. v. Monfort of Colo., Inc.*, 479 U.S. 104, 121 n.17 (1986).

Standard Oil did not use predatory pricing to monopolize the market. Long before the advent of pricing algorithms, dominant firms used below-cost pricing strategies to monopolize markets.²⁹⁸ Predatory pricing has happened in the past, and it's more likely to occur in the future.

Monopolists should be liable for violating Section Two of the Sherman Act whenever they use below-cost pricing to acquire or maintain their monopoly power, or if their use of predatory pricing creates a dangerous probability of monopolization. Because the ability to price discriminate effectively through AI reinforces the market power of dominant platforms, below-cost pricing should be considered predatory regardless of whether the pricing decisions are made by machines or humans.

Coupled with inappropriately pro-defendant predatory pricing doctrine, the growth and evolution of pricing algorithms could presage a renaissance of price predation. Pricing algorithms make predatory pricing schemes both easier to implement and harder to detect. Federal judges need to be prepared to properly adjudicate monopolization claims based on algorithmic predation. This Part discusses some doctrinal and policy changes to assist in achieving that goal: examining individual transactions, requiring retention of pricing records, and eliminating the recoupment element.

A. *The Significance of Individual Transactions*

In addition to the other traditional elements of a Section Two claim, antitrust plaintiffs must prove two unique elements of a predatory pricing claim: that the defendant charged a price below its costs and the defendant had a dangerous probability of recoupment.²⁹⁹ The first element of below-cost pricing remains contentious because the Supreme Court has now articulated the element three times, yet the Court has demurred every single time to define what it means by

²⁹⁸ See Vaheesan, *supra* note 43, at 84–94 (providing numerous historical examples of predatory pricing); Richard O. Zerbo, Jr. & Michael T. Mumford, *Does Predatory Pricing Exist? Economic Theory and the Courts After Brooke Group*, 41 ANTITRUST BULL. 949, 958 (1996); Edward H. Cooper, *Attempts and Monopolization: A Mildly Expansionary Answer to the Prophylactic Riddle of Section Two*, 72 MICH. L. REV. 373, 436 & n.232 (1974) (discussing several cases characterized as involving “clear or highly probable” anticompetitive below-cost pricing); see also Thomas W. Hazlett, *Predation in Local Cable TV Markets*, 40 ANTITRUST BULL. 609 (1995) (discussing a case study of price predation); *Springfield Terminal Ry. Co. v. Canadian Pac. Ltd.*, 133 F.3d 103, 106 (1st Cir. 1997); Richard T. Rapp, *Predatory Pricing Analysis: A Practical Synthesis*, 59 ANTITRUST L.J. 595, 596 (1991); Bolton et al., *supra* note 218, at 2505.

²⁹⁹ The elements of a Section Two claim include proving the defendant's monopoly power and that the plaintiff suffered antitrust injury. See *supra* Section I.A.

“cost.”³⁰⁰ Scholars have debated what the appropriate measure of cost should be.³⁰¹ And different circuits have adopted different standards.³⁰²

However “costs” are defined, courts need to focus on the relevant transactions—those sales that took place at a price below cost. When evaluating the first element of a predatory pricing claim, some federal courts tend to look at the defendant’s aggregate profitability across all sales. For example, federal courts have held that “[a] predatory pricing plaintiff can prevail only by adducing ‘evidence suggesting defendants’ overall price structure was predatory,’ not that a small minority of sales were below average variable cost.”³⁰³ In the context of airline predatory pricing, the Tenth Circuit rejected antitrust claims against American Airlines because “American did not price below AVC for any route *as a whole*”³⁰⁴ The Tenth Circuit focused on the profitability of each American route, not individual transactions. But this is the wrong measure. A predator could sell tickets for individual seats at a loss in order to peel off marginal flyers and prevent its rival from reaching minimum efficient scale. By failing to consider this possibility, the Tenth Circuit misanalyzed the issue: Later statements by American Airlines’s CEO show that it was, in fact, engaging

³⁰⁰ *Brooke Grp. Ltd. v. Brown & Williamson Tobacco Corp.*, 509 U.S. 209, 222 n.1 (1993) (first citing *Cargill, Inc. v. Monfort of Colo., Inc.*, 479 U.S. 104, 117–18 n.12 (1986); and then citing *Matsushita Elec. Indus. Co. v. Zenith Radio Corp.*, 475 U.S. 574, 585 n.8 (1986)) (“Because the parties in this case agree that the relevant measure of cost is average variable cost, however, we again decline to resolve the conflict among the lower courts over the appropriate measure of cost.”).

³⁰¹ See, e.g., Philip Areeda & Donald F. Turner, *Predatory Pricing and Related Practices Under Section 2 of the Sherman Act*, 88 HARV. L. REV. 697, 716–18 (1975) (advocating that average variable costs be used as a proxy for marginal costs). Compare Aaron S. Edlin, *Stopping Above-Cost Predatory Pricing*, 111 YALE L.J. 941 (2002), with Einer Elhauge, *Why Above-Cost Price Cuts to Drive Out Entrants Are Not Predatory—and the Implications for Defining Costs and Market Power*, 112 YALE L.J. 681, 711–14 (2003) (debating whether above-cost price cuts can be predatory).

³⁰² Compare *Arthur S. Langenderfer, Inc. v. S.E. Johnson Co.*, 729 F.2d 1050, 1056 (6th Cir. 1984) (applying “the Ninth Circuit’s modification of the ‘Areeda/Turner’ rule”), with *McGahee v. N. Propane Gas Co.*, 858 F.2d 1487, 1495 (11th Cir. 1988) (describing the Areeda-Turner test as like the Venus de Milo: “much admired and often discussed, but rarely embraced” (footnote omitted)).

³⁰³ *Ramallo Bros. Printing v. El Dia, Inc.*, 392 F. Supp. 2d 118, 140 (D.P.R. 2005) (quoting *Morgan v. Ponder*, 892 F.2d 1355, 1361 (8th Cir. 1989)); see also *Directory Sales Mgmt. Corp. v. Ohio Bell Tel. Co.*, 833 F.2d 606, 614 (6th Cir. 1987) (holding that “the relevant area of inquiry should be [the defendant’s] operations taken as a whole”); *Wal-Mart Stores, Inc. v. Am. Drugs, Inc.*, 891 S.W.2d 30, 33 (Ark. 1995) (noting that despite below-cost sales of some products, the defendant’s “overall product line for pharmaceuticals and health and beauty aids was sold above cost, and its pharmacy was profitable”).

³⁰⁴ *United States v. AMR Corp.*, 335 F.3d 1109, 1120 (10th Cir. 2003) (emphasis added).

in price predation to destroy rival discount airlines.³⁰⁵ Using pricing algorithms, airlines can target just those price-sensitive travelers who would otherwise purchase tickets on a discount airline.³⁰⁶ The fact that an overall flight or route is profitable is irrelevant if the predator is using below-cost pricing to poach its rivals' customers.³⁰⁷ In non-airline cases, some judges decline to look at individual products that are sold below cost when the defendant offers a larger line of products, many or most of which are sold at above-cost prices.³⁰⁸ Still other federal courts have suggested that below-cost pricing targeted to a few customers is unlikely to have an anticompetitive effect.³⁰⁹ These opinions do not explain why the defendant would willingly incur losses without an expectation of recoupment.

Algorithmic price predation involves *targeted* below-cost pricing. This personalized price predation can allow a dominant firm to tempt its rivals' customers away while maintaining overall profitability by

³⁰⁵ Indeed, American's CEO justified its profit-reducing strategy of expanding operations and reducing prices as a means to drive rivals from the market entirely, stating, "If you are not going to get [Low Cost Carriers] out then no point to diminish profit." Aaron S. Edlin, *Predatory Pricing: Limiting Brooke Group to Monopolies and Sound Implementation of Price-Cost Comparisons*, 127 YALE L.J.F. 996, 1007–08 (2018).

³⁰⁶ Airlines already use algorithmic, dynamic pricing.

³⁰⁷ Cf. Elhauge, *supra* note 301, at 731 ("[U]nder a cost-based test, the prices a hub-and-spoke airline charges should not be considered predatory unless the overall revenue on a hub-and-spoke system falls below the cost of providing the entire hub-and-spoke system.").

³⁰⁸ See *Fisherman's Wharf Bay Cruise Corp. v. Superior Ct. of S.F.*, 7 Cal. Rptr. 3d 628, 641 (Cal. Ct. App. 2003) ("In determining whether sales are made 'below cost,' the prevailing analysis under federal antitrust law . . . is not performed on a product-by-product basis, but across an entire line of products sold by the defendant[,] . . . focus[ing] on whether . . . the below-cost sales pose a genuine threat to the overall competition." (collecting cases)); see, e.g., *Morgan v. Ponder*, 892 F.2d 1355, 1362 (8th Cir. 1989) ("Courts have been wary of plaintiffs' attempts to prove predatory pricing through evidence of a low price charged for a single product out of many, or to a single customer."); *Janich Bros., Inc. v. Am. Distilling Co.*, 570 F.2d 848, 856 (9th Cir. 1977) (rejecting predatory pricing claim in alcoholic beverages market because "pricing of one size at a predatory level would not necessarily drive out rivals who were selling a full line" of sizes); see also Garret G. Rasmussen, *Antitrust Implications of Cases Rejecting Cross-Subsidization Arguments*, ANTITRUST, Fall 1988, at 28, 31 (describing *Janich Brothers* as "agree[ing] with the defendant, a nationwide distributor of alcoholic beverages, that although it had sold half-gallon bottles of alcohol at below cost prices, its losses should be ignored in light of the profitability of its overall line").

³⁰⁹ See, e.g., *Taylor Publ'g Co. v. Jostens, Inc.*, 216 F.3d 465, 478 (5th Cir. 2000) (rejecting plaintiff's predatory pricing claims because the defendant's below-cost pricing was targeted to a small percentage of plaintiff's customer base); *Ramallo Bros. Printing v. El Dia, Inc.*, 392 F. Supp. 2d 118, 140 (D.P.R. 2005) ("Predation claims cannot be based on occasional instances of allegedly predatory pricing, because they are not likely to drive rivals from the market and to permit the predator to raise prices and profits subsequently."); see also *Stearns Airport Equip. Co. v. FMC Corp.*, 170 F.3d 518, 529 (5th Cir. 1999) (ultimately rejecting plaintiff's argument that "even small amounts of predation are not permissible under the antitrust laws").

charging money-making prices to its current customers. In analyzing the first element of a predatory pricing claim, federal courts should examine the prices charged to the targets of the alleged predation, not the profitable sales that are funding the war chest. In interpreting state prohibitions against predatory pricing, some state courts have “analyzed the challenged sales based upon the *actual* below-cost prices charged for a product or service, without regard to whether other above-cost sales on identical or similar products made the overall enterprise profitable.”³¹⁰ While state antitrust law can differ from federal law,³¹¹ this state approach is the correct one. As Professors Areeda and Hovenkamp have explained, below-cost prices are generally “irrational unless they are intended to destroy or discipline rivals in anticipation of later monopoly prices.”³¹² If the targeted price predation has the effect of driving a rival from the market, the below-cost prices injure competition even if the defendant’s overall operations remain profitable.

While pricing algorithms increase the feasibility of predators simultaneously engaging in below-cost sales and profitable sales, some algorithmic predators will try to recoup their early losses by charging supracompetitive prices for replacement items.³¹³ When predators seek recoupment in subsequent sales, courts should be certain to analyze the below-cost sales separately from above-cost sales when determining whether the plaintiff has satisfied the first element of a predatory pricing claim. Unfortunately, courts in the pre-algorithmic era sometimes commingled these sales. For example, in *Stitt Spark Plug Co. v. Champion Spark Plug Co.*, the plaintiff challenged the defendant’s practice of selling a first set of spark plugs at below-cost and then charging a monopoly price for replacement plugs.³¹⁴ Despite the fact that the original spark plugs were sold at a loss, the Fifth Circuit improperly held that there was no below-cost pricing because the monopolist knew it would recoup these losses in the replacement market.³¹⁵ This approach renders the first and second elements of a

³¹⁰ *Fisherman’s Wharf Bay Cruise Corp.*, 7 Cal. Rptr. at 642.

³¹¹ See *id.* at 641 (“But these *federal* authorities relied on heavily by Blue & Gold do not convince us that below-cost pricing for even a limited number of customers, or a market segment, falls outside of the reach of our *state’s* antitrust law simply because the overall enterprise remains profitable.”).

³¹² Areeda & Hovenkamp, *supra* note 64, ¶ 727(f), at 96.

³¹³ See *supra* Section II.B.3.b.

³¹⁴ 840 F.2d 1253, 1255 (5th Cir. 1988).

³¹⁵ *Id.* at 1256 (“When Champion sets the prices for original-equipment plugs, the expected return includes not only the price paid by the original-equipment manufacturer, but also the replacement purchases that probably will follow. Hence, any meaningful comparison of price and cost must encompass Champion’s sales to both markets.”).

predatory pricing claim mutually exclusive: either the defendant recoups and the scheme isn't predatory (and Element #1 is not met), or the defendant does not recoup (and Element #2 is not met).³¹⁶ Regrettably, the Fifth Circuit is not the only court to improperly obscure losing sales with the existence of profitable sales.³¹⁷ Courts adjudicating claims of algorithmic predatory pricing should avoid this mistake. The first element is satisfied whenever a dominant firm uses below-cost pricing to steal sales from a rival, regardless of whether other current or future sales are profitable.

B. *Discovery in the Algorithmic Age*

Whatever the appropriate measure of costs is, plaintiffs will require meaningful discovery of both cost and price to prove below-cost pricing. But if the monopolist has used a predatory pricing algorithm, then both sets of data are distinctively within its control. In the past, antitrust plaintiffs could generally discern price without much discovery.³¹⁸ But assessing prices could be more difficult in the era of algorithms because sellers do not charge one set price. Personalized dynamic pricing means a single product can have hundreds of different prices that vary by consumer.³¹⁹ Some prices could be below cost, others not.

Dynamic pricing further complicates the first element of a predatory pricing claim. Plaintiffs cannot easily look up “the price” during the predation period. With prices constantly changing, plaintiffs will face greater difficulty proving the actual transaction prices the defendant charged.³²⁰ Access to all relevant pricing data will prove more complicated when plaintiffs bring algorithmic predatory pricing claims.

Pricing algorithms increase the importance of pretrial discovery in predatory pricing litigation. Document discovery is often critical for

³¹⁶ Leslie, *supra* note 32, at 1726 (explaining why this scenario is a Catch-22 for antitrust plaintiffs).

³¹⁷ See *Kentmaster Mfg. Co. v. Jarvis Prods. Corp.*, 146 F.3d 691, 694–95 (9th Cir. 1998), *amended*, 164 F.3d 1243 (9th Cir. 1999) (treating below-cost sales of original equipment and above-cost sales of replacement parts as a “single product” and concluding that the defendant’s overall profitability meant that its pricing was “not predatory”).

³¹⁸ *Cf. Crane*, *supra* note 30, at 41 (“Predator firms should expect that their conduct will not go unnoticed.”).

³¹⁹ See Ramsi A. Woodcock, *Personalized Pricing as Monopolization*, 51 CONN. L. REV. 311, 313 (2019) (noting that Amazon “varies the prices of thousands of items hundreds of time[s] per day”).

³²⁰ Khan, *supra* note 138, at 763–64; *id.* at 764 (“Discerning whether and by how much Amazon raises book prices will be more difficult than the *Matsushita* or *Brooke Group* Courts could have imagined.”).

antitrust plaintiffs.³²¹ Discovery generally entails asymmetric dynamics because defendants control the essential documents.³²² This is particularly true in predatory pricing claims where the defendants uniquely understand their costs, prices, and whether they have charged a price below cost. The plaintiffs may be able to discern neither the defendants' cost nor various prices without accessing the defendants' internal records.

To ensure that colorable claims proceed appropriately, courts should take three actions in cases involving predatory pricing algorithms. First, courts should require defendants to produce their price and cost data in a format that is straightforward to comprehend and interpret. Records should clearly indicate the transaction prices actually paid by consumers.

Second, and relatedly, judges should ensure that firms do not destroy their pricing records. Unfortunately, antitrust violators routinely destroy incriminating records in order to evade liability.³²³ Document destruction can be cost-beneficial because courts do not sufficiently penalize spoliation.³²⁴ That trend warrants reversal. Whether through administrative rules or some other tool, firms should have to keep easily discoverable records of their prices offered and charged to consumers. While retention of paper records could impose unreasonable burdens on firms, electronic records are more easily and affordably stored and retained.

Third, a defendant's pricing algorithms themselves should be subject to discovery. The below-cost price can be traced back to the algorithm's code.³²⁵ Records relating to pricing algorithms may pre-

³²¹ *In re Uranium Antitrust Litig.*, 480 F. Supp. 1138, 1155 (N.D. Ill. 1979) (“[T]he heart of any American antitrust case is the discovery of business documents. Without them, there is virtually no case.” (quoting Timothy G. Smith, Note, *Discovery of Documents Located Abroad in U.S. Antitrust Litigation: Recent Developments in the Law Concerning the Foreign Illegality Excuse for Non-Production*, 14 VA. J. INT’L L. 747, 747 (1974))).

³²² Mark A. Lemley & Christopher R. Leslie, *Antitrust Arbitration and Merger Approval*, 110 NW. U. L. REV. 1, 16–17 (2015) (“Antitrust litigation often involves document asymmetry in that the defendant is rarely going to need critical documents from the plaintiff while the plaintiff’s case may turn on the smoking gun in the defendants’ files.”).

³²³ See Christopher R. Leslie, *How to Hide a Price-Fixing Conspiracy: Denial, Deception, and Destruction of Evidence*, 2021 U. ILL. L. REV. 1199, 1221–23 (2021) (discussing records destruction to conceal Section One violations).

³²⁴ See *id.* at 1251–53 (arguing that a “burden of proof” which “rewards price-fixing defendants who destroy documents” is illustrative of “how courts approach the issue of document destruction in price-fixing cases”).

³²⁵ MacKay & Weinstein, *supra* note 76, at 141 (“In practice, algorithms often have less flexibility and are restricted by a set of rules that are encoded in software. These rules may be quite complicated, and they may evolve over time. Regardless, the chosen price can be traced directly to underlying code.” (footnote omitted)).

sent discovery issues as well because pricing algorithms are often proprietary,³²⁶ and firms keep their pricing algorithms secret.³²⁷ Courts have held that pricing algorithms can be trade secrets.³²⁸ In non-predatory pricing cases, courts appear reluctant to order antitrust defendants to produce their pricing algorithms.³²⁹ This reluctance must be overcome when the algorithm itself is the weapon of predatory pricing. A defendant's legitimate concerns can be protected by having algorithms produced subject to confidentiality restrictions and protective orders.

C. *The Irrelevance of Recoupment*

Antitrust doctrine that makes predatory pricing claims difficult—to pursue is based on the assumption that firms do not engage in below-cost pricing strategies because they are doomed to fail. The recoupment requirement represents the greatest barrier to plaintiffs bringing valid predatory pricing claims.

Courts have justified the recoupment requirement for three reasons, all of them incorrect. First, courts assert the recoupment requirement is necessary to prevent predatory pricing claims from proceeding

³²⁶ *Id.* at 125 (“Many sophisticated firms have developed their own proprietary pricing algorithms.”); *see, e.g., id.* (“Large online retailers like Walmart and eBay also employ proprietary algorithms on their e-commerce platforms.” (citing Cem Dilmegani, *Dynamic Pricing: How Does It Work & How to Implement It*, AI MULTIPLE (July 25, 2022), <https://research.aimultiple.com/dynamic-pricing> [<https://perma.cc/9GYQ-JWNC>])); Calo & Rosenblat, *supra* note 128 at 1656 (“Uber determines a price according to a proprietary surge-pricing algorithm.”).

³²⁷ *See, e.g.,* Cotter v. Lyft, Inc., No. 13-cv-04065, 2016 WL 3654454, at *2 (N.D. Cal. June 23, 2016) (“And while Lyft may be correct that its competitors could gain an unfair advantage against it if they knew the precise contours of its pricing algorithms, as the Gibson declaration indicates, Lyft’s ‘proprietary pricing models’ consist of ‘various components,’ including many undisclosed inputs.”); Rodman v. Safeway Inc., 125 F. Supp. 3d 922, 941 (N.D. Cal. 2015), *aff’d*, 694 F. App’x 612 (9th Cir. 2017) (“Class members did not even possess means of discovering this knowledge, as Safeway’s online pricing algorithm was not publicly disclosed.”); *In re Elec. Books Antitrust Litig.*, No. 11 MD 2293, 2014 WL 1282293, at *56 (S.D.N.Y. Mar. 28, 2014) (“Amazon’s pricing algorithm . . . is proprietary . . .”).

³²⁸ *E.g.,* Medidata Sol., Inc. v. Veeva Sys., Inc., No. 17 Civ. 589, 2021 WL 467110, at *9 (S.D.N.Y. Feb. 9, 2021) (“A reasonable juror could evaluate Medidata’s description of [its proprietary pricing algorithm] to determine whether Medidata seeks to protect a particular item of pricing information as a trade secret.”); *cf. Free Country LTD v. Drennen*, 235 F. Supp. 3d 559, 566–67 (S.D.N.Y. 2016) (finding pricing information were not trade secrets, in part, because there was no complex pricing algorithm); *2KDirect, LLC v. Azoogles Ads US, Inc.*, No. CV 08-3340-VB, 2010 WL 11455972, at *4 (C.D. Cal. Apr. 19, 2010) (finding “triable issue of fact as to whether Plaintiffs’ Pricing Algorithm derived value from being secret”).

³²⁹ *See, e.g., In re Int. Rate Swaps Antitrust Litig.*, No. 16-MD-2704, 2019 WL 7584653, at *1 (S.D.N.Y. Nov. 21, 2019).

to trial because predatory pricing does not happen.³³⁰ But firms in fact have used below-cost pricing to vanquish rivals and monopolize markets.³³¹ By minimizing the losses during the predation phase and maximizing profits during the recoupment phase, algorithmic pricing increases the attractiveness and likelihood of predatory pricing.

Second, courts claim that absent recoupment, below-cost pricing cannot harm consumers.³³² Indeed, several opinions praise failed predatory pricing schemes as a boon for consumers.³³³ This thinking is flawed because those consumers who pay a monopoly price during the recoupment phase of a predatory pricing scheme suffer antitrust injury regardless of whether the consumers who paid a below-cost price during the predation phase saved more money than the later consumers were overcharged.³³⁴ Consumers are always injured during the recoupment phase, independent of the predator's profitability.

³³⁰ See *Stitt Spark Plug Co. v. Champion Spark Plug Co.*, 840 F.2d 1253, 1255 (5th Cir. 1988) (“The [*Matsushita*] Court [held] that the economic disincentives to predatory pricing often will justify a presumption that an allegation of such behavior is implausible.”); see also Timothy J. Trujillo, Note, *Predatory Pricing Standards Under Recent Supreme Court Decisions and Their Failure to Recognize Strategic Behavior as a Barrier to Entry*, 19 J. CORP. L. 809, 820 (1994) (“The Court’s recoupment standard is premised upon the theory that ‘predatory pricing schemes are rarely tried, and even more rarely successful,’ and, as a result, the prerequisites to recovery are purposefully difficult to establish.” (footnote omitted) (citing *Matsushita Elec. Indus. Co. v. Zenith Radio*, 475 U.S. 574, 589 (1986))); *Advo, Inc. v. Phila. Newspapers, Inc.*, 51 F.3d 1191, 1196 (3d Cir. 1995) (“While it was once believed that turn-of-the-century ‘robber barons’ commonly practiced predatory pricing to eliminate competitors, research over the last few decades has exposed this belief as a myth.”); see also *id.* (“*Matsushita* . . . created a legal presumption, based on economic logic, that predatory pricing is unlikely to threaten competition.” (emphasis omitted)).

³³¹ See, e.g., *supra* note 305 and accompanying text.

³³² E.g., *W. Parcel Express v. United Parcel Serv.*, 65 F. Supp. 2d 1052, 1063 (N.D. Cal. 1998) (“Predatory pricing is only harmful when the predator succeeds in recouping the losses it suffered by its earlier below-cost pricing.”), *aff’d*, 190 F.3d 974 (9th Cir. 1999).

³³³ *Brooke Group Ltd. v. Brown & Williamson Tobacco Corp.*, 509 U.S. 209, 224 (1993) (“[P]redatory pricing produces lower aggregate prices in the market, and consumer welfare is enhanced.”); *A.A. Poultry Farms, Inc. v. Rose Acre Farms, Inc.*, 881 F.2d 1396, 1401 (7th Cir. 1989) (“Price less than cost today, followed by the competitive price tomorrow, bestows a gift on consumers. Because antitrust laws are designed for the benefit of consumers, not competitors, a gift of this kind is not actionable.” (citation omitted)); *Advo*, 51 F.3d at 1200 (“Such futile below-cost pricing effectively bestows a gift on consumers, and the Sherman Act does not condemn such inadvertent charity.”); see also *Atl. Richfield Co. v. USA Petroleum Co.*, 495 U.S. 328, 340 (1990) (“Low prices benefit consumers regardless of how those prices are set.”).

³³⁴ AREEDA & HOVENKAMP, *supra* note 64, ¶ 726(d)(4), at 77 (“[P]ost-predation prices can be significantly supracompetitive, thereby injuring consumers, and yet be insufficient in size or duration to provide full recoupment for the defendant’s investment in predation.”); Leslie, *supra* note 32, at 1742 (“Consumers paying monopoly prices in the post-predation period are injured even if the monopoly price is insufficient to recoup the investment in predatory pricing.”).

Third, federal courts routinely assert that “[w]ithout a dangerous probability of recoupment, competition remains unharmed even if individual competitors suffer.”³³⁵ This is incorrect because predatory pricing is inefficient whether or not the predator recoups its losses.³³⁶ The tragedy of the recoupment requirement is that it is entirely extraneous to whether a dominant firm’s below-cost pricing has inflicted antitrust injury. If a monopolist acquires or maintains its monopoly power by driving its rivals from the market through predatory pricing, those vanquished rivals have suffered anticompetitive harm by being excluded from the market for reasons unrelated to efficiency or competition on the merits. Those harms remain unaffected by whether the monopolist recoups its losses from pricing below cost during the predation phase.³³⁷

Beyond its flawed premises, the recoupment requirement has always been problematic because courts do not apply it well. For example, courts have consistently failed to appreciate how predatory firms can recoup their losses for below-cost pricing in the markets for complementary products and substitute products, or through cartel or oligopoly pricing.³³⁸ Mistakes are common. Indeed, in *Brooke Group*, the Supreme Court case creating the recoupment requirement, the majority asserted that recoupment was improbable despite evidence showing that recoupment had probably already occurred.³³⁹

The recoupment requirement is even more susceptible to misapplication in the context of algorithmic predation. Judges unversed in algorithms may not grasp how firms can use AI to manipulate consumer decisions and reduce choices. Many people seem to believe that internet shopping is inherently competitive because rivals are “just [a] click away[.]”³⁴⁰ but this belief is facile and naïve because dominant

³³⁵ *E.g.*, *United States v. AMR Corp.*, 335 F.3d 1109, 1115 (10th Cir. 2003).

³³⁶ *Leslie*, *supra* note 32, at 1743 (“Predatory pricing also causes inefficiency, regardless of whether the predator recoups its investment.”).

³³⁷ *See id.* at 1761 (“A predator may become a monopolist but not recoup its investment in predatory pricing.”).

³³⁸ *See id.* at 1720–38 (cataloguing cases where courts failed to appreciate the possibility of recoupment in complementary product markets, in substitute product markets, or through cartel or oligopoly pricing).

³³⁹ *Id.* at 1737.

³⁴⁰ John M. Newman, *Antitrust in Digital Markets*, 72 *VAND. L. REV.* 1497, 1518 (2019) (“[A]nti-enforcement scholars and stakeholders contend that digital markets should evade antitrust scrutiny because ‘competition is just [a] click away.’” (quoting Adam Kovacevich, *Google’s Approach to Competition*, *GOOGLE PUB. POL’Y BLOG* (Mar. 8, 2009), <https://publicpolicy.googleblog.com/2009/05/googles-approach-to-competition.html> [<https://perma.cc/WYP8-4UKD>])).

firms can impose and manipulate switching costs that render rivals a click too far.³⁴¹

Judges may not appreciate some of the specific recoupment methods that an algorithmic price predator may utilize. For example, judges do not necessarily comprehend the dynamics of recoupment through replacement products, which dominant platforms could exploit through algorithm-driven restocking.³⁴² In the pre-internet case challenging Champion's attempted monopolization of the spark plug market, the Fifth Circuit affirmed a directed verdict for the defendant because the judges did not appreciate how Champion had perfected a predatory pricing scheme.³⁴³ The Supreme Court had already explained the dynamics of brand-specific replacement in this well-studied market.³⁴⁴ Courts are even more likely to overlook this method of recoupment in cyberspace markets that are far more complicated. If so, this will allow algorithmic price predators to improperly escape antitrust liability.

In sum, the advent of algorithmic pricing should force courts to revisit their misconceptions about the plausibility of predatory pricing claims, including eliminating those elements—such as the recoupment requirement—that make such claims impossible to pursue based on the false premise that price predation is implausible.

CONCLUSION

Despite considering it, the U.S. military never relied on computers to initiate and fight nuclear wars. That bridge not crossed in nuclear strategy now spans cyberspace and is traversed thousands of times a day as more and more businesses rely on pricing algorithms to maximize sales and profits. This magnifies the risk of algorithmic predatory pricing.

Economic theories on the implausibility of predatory pricing rest upon three pillars of assumption: First, the predator will incur asymmetric losses; second, predatory threats are not credible; and third, recoupment is implausible. Pricing algorithms undermine all three pillars.

³⁴¹ See *supra* notes 265–66 and accompanying text.

³⁴² See *supra* notes 234–39 and accompanying text.

³⁴³ See Leslie, *supra* note 32 at 1725–26 (critiquing the Fifth Circuit's opinion in *Stitt Spark Plug Co. v. Champion Spark Plug Co.*, 840 F.2d 1253 (5th Cir. 1988), which had reasoned that because Champion would recoup its losses in the market for replacement plugs it was not losing money in the OE plug market and, thus, not engaging in predatory pricing).

³⁴⁴ *Ford Motor Co. v. United States*, 405 U.S. 562, 565 (1972).

Pricing algorithms allow firms to limit their losses during the predation phase by precisely targeting their below-cost prices. Predatory price discrimination is far easier now than when Standard Oil and American Tobacco targeted their rivals' customers for extraordinary deals. Pricing algorithms can address the targeting problem without setting up bogus companies. The expensive espionage network maintained by John D. Rockefeller and his lieutenants are no longer needed. A sufficiently powerful pricing algorithm can do the work of an army of spies and tacticians. Algorithms can communicate commitment and hasten recoupment of the (algorithm-minimized) losses incurred.

In light of advances in artificial intelligence, it is time to revisit and reevaluate antitrust doctrine based on theories of predatory pricing being inconceivable. These theories were wrong when first announced, and they are increasingly outdated in the era of algorithms. Now is the time to abandon outmoded theories about the implausibility of predatory pricing and to reject legal rules based on these theories.