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ALGORITHMIC PREDATION AND EXCLUSION

Thomas K. Cheng* and Julian Nowag**

| | |
|---|----|
| I. INTRODUCTION | 43 |
| II. ALGORITHMIC TARGETING AND NEW FRONTIERS OF PREDATORY AND EXCLUSIONARY CONDUCT | 45 |
| A. An Upstream Case Study: Hell—Predation and Rebates at Work and the Feasibility of Personalized Pricing | 46 |
| B. Other Forms of Targeted Exclusionary Conduct..... | 51 |
| 1. Predatory Pricing | 51 |
| 2. Anticompetitive Targeted Rebates..... | 51 |
| 3. Tying and Bundling | 52 |
| C. The Core Challenges of Algorithmic Targeting..... | 53 |
| III. ALGORITHMIC TARGETING AND PREDATORY PRICING | 55 |
| A. Recoupment: Possible Current Approaches | 55 |
| 1. The Direct Approach..... | 56 |
| a. Predation loss | 57 |
| b. Post-predation gains..... | 58 |
| 2. The Indirect Approach | 60 |
| B. Algorithmic Targeting and Recoupment..... | 61 |
| 1. General Impact..... | 61 |
| 2. Impact on the Indirect Approach | 64 |
| 3. Impact on the Direct Approach..... | 66 |
| a. Actual profit standards | 66 |
| b. Hypothetical profit standards | 67 |
| c. Options for adjustments | 67 |
| i. Abandonment of the actual profit standards | 67 |
| ii. Adjusting the actual profit standards | 68 |
| iii. Abolishing the recoupment requirement | 70 |

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| | |
|--|-----|
| C. Algorithmic Targeting and the Appropriate Price for Price-Cost Comparison | 78 |
| D. Algorithmic Targeting and the Appropriate Cost Measure 80 | |
| 1. The Appropriate Cost Measure: The Existing Debate 80 | |
| a. Marginal cost | 81 |
| b. Average variable cost..... | 82 |
| c. Average incremental cost and average avoidable cost | 84 |
| 2. The Appropriate Cost Measure in the World of Algorithmic Targeting | 85 |
| IV. ALGORITHMIC TARGETING AND ANTICOMPETITIVE REBATES | 89 |
| V. ALGORITHMIC TARGETING AND TYING AND BUNDLING..... | 91 |
| A. Tying in the Pre-digital World..... | 91 |
| B. Tying in the World of Algorithmic Targeting | 93 |
| 1. Tying Feasible at Lower Level of Market Power | 93 |
| 2. Facilitation of Offensive Leveraging | 94 |
| 3. Variable-proportions Ties No Longer Needed to Accomplish Price Discrimination | 97 |
| VI. ALGORITHMIC TARGETING AND THE AS-EFFICIENT COMPETITOR TEST | 98 |
| VII. CONCLUSION | 100 |

The debate about the implications of algorithms on antitrust law enforcement has so far focused on multi-firm conduct in general and collusion in particular. The implications of algorithms on abuse of dominance have been largely neglected.¹ This article seeks to fill this gap in the existing literature by exploring how the increasingly precise practice of individualized targeting by algorithms can facilitate the practice of a range of abuses of dominance, including predatory pricing, rebates, and tying and bundling. The ability to target disparate groups of consumers with different prices helps a predator to minimize the losses it sustains during predation and maximize its ability to recoup its losses. This changes how recoupment should be understood and ascertained and may even undermine the rationale for requiring a proof of likelihood of recoupment under U.S. antitrust law. This increased ability to price discriminate also enhances a dominant firm's ability to offer exclusionary rebates. Finally, algorithms allow dominant firms to target their tying and bundling practices to loyal customers, hence avoiding the risk of alienating marginal customers with an unwelcome tie.

1. For a notable exception, see Christopher R. Leslie, *Predatory Pricing Algorithms*, 97 N.Y.U. L. REV. (forthcoming 2022).

This renders tying and bundling more feasible and effective for dominant firms.

I. INTRODUCTION

Virtual Competition by Ariel Ezrachi and Maurice Stucke² can be seen to have brought the attention of the antitrust law community to the issues of algorithms and big data.³ Since the publication of the book, much research has focused on the prospect of collusive behavior facilitated by the emergence of artificial intelligence. Countless papers have been published all over the world on algorithmic collusion and how antitrust law should respond to the phenomenon. The discussion has ranged from the feasibility of algorithmic collusion to how should antitrust law respond to this competitive threat. It has been suggested that it is possible for algorithms to communicate with each other and learn to engage in tacit collusion as an intelligent response to the task of profit maximization without being explicitly instructed by human agents to do so. Given the ability of algorithms to monitor thousands of price points at any given point in time and to detect and respond almost instantaneously to defections by rivals, algorithms can turbo-charge tacit collusion and threaten to make it a reality outside of highly oligopolistic markets selling homogenous products.

Meanwhile, the possible impact of the use of algorithms by dominant firms to pursue monopolistic conduct and abuses of dominance has been largely overlooked.⁴ Although there are limits to the current capability of algorithms, technology is progressing fast. In the future, it may well progress to such an extent that algorithms, with the help of big data, can accurately identify marginal and inframarginal customers or perhaps even assess an individual consumer's willingness to pay. The cutting edge of research on

2. ARIEL EZRACHI & MAURICE E. STUCKE, *VIRTUAL COMPETITION* (2016).

3. See, e.g., Francisco Beneke & Mark-Oliver Mackenrodt, *Remedies for Algorithmic Tacit Collusion*, 9 J. ANTITRUST ENFORCEMENT 152 (2021); Emilio Calvano et al., *Artificial Intelligence, Algorithmic Pricing, and Collusion*, 110 AM. ECON. REV. 3267, 3267–68 (2020); Marixenia Davilla, *Is Big Data a Different Kind of Animal? The Treatment of Big Data Under the EU Competition Rules*, 8 J. EUR. COMPETITION L. & PRAC. 370, 370 (2017); Michal S. Gal, *Algorithms as Illegal Agreements*, 34 BERKELEY TECH. L.J. 67, 67–118 (2019); Karsten T. Hansen et al., *Frontiers: Algorithmic Collusion: Supra-competitive Prices via Independent Algorithms*, 40 MKTG. SCI. 1, 1 (2021); Wolfgang Kerber, *Digital Markets, Data, and Privacy: Competition Law, Consumer Law and Data Protection*, 11 J. INTELL. PROP. L. & PRAC. 856, 856 (2016); Ulrich Schwalbe, *Algorithms, Machine Learning, and Collusion*, 14 J. COMPETITION L. & ECON. 568, 569, 572, 591 (2019); MAURICE E. STUCKE & ALLEN P. GRUNES, *BIG DATA AND COMPETITION POLICY*, at v (2016); Beata Mähäniemi, *COMPETITION LAW AND BIG DATA: IMPOSING ACCESS TO INFORMATION IN DIGITAL MARKETS* 34 (2020).

4. See however Leslie, *supra* note 1.

artificial intelligence (AI) has moved on to what are known as “foundation models.”⁵ Eighty percent of the latest AI research is reportedly focused on these models.⁶ One of the major breakthroughs of these models is their ability to conduct self-supervised learning, which obviates the need for humans to label the data sets that are fed into the machines in advance.⁷ The latest foundation model, called PALM, was released by Google in April 2022 and is reportedly capable of processing 540 billion parameters.⁸ At the rate AI technology is progressing, precise customer segmentation seems to be a matter of when and not if. Precise segmentation of customers will greatly improve a dominant firm’s ability to pursue predatory and exclusionary conduct. Without such precise customer segmentation, a dominant firm must pursue predation and exclusionary conduct across the board in the market. This necessitates a trade-off between the additional profit from inframarginal customers who stay loyal to the firm’s product and the potential loss of profit from the defection of marginal customers. The effectiveness and profitability of predatory and exclusionary conduct is constrained by this tradeoff.

Legal doctrines on conduct, such as predatory pricing, rebates, and tying and bundling, are structured in ways that implicitly reflect this tradeoff. As will be demonstrated in this article, specific targeting of customers that may be made possible in the future by the use of algorithms and big data, hereinafter referred to as “algorithmic targeting,” would significantly reduce the acuteness of this tradeoff if not eliminate it altogether. Algorithmic targeting would shake the foundations of these legal doctrines and would call for a fundamental rethink in the way antitrust law should analyze a range of predatory and exclusionary conduct. By way of example, more targeted pricing practices would allow a dominant firm to pursue predatory pricing in a much more targeted manner such that the predation loss can be minimized, which in turns renders recoupment more likely. This may alter the application of the recoupment requirement under the current doctrine on predatory pricing in the United States.

We first explore the current capabilities of algorithms by looking at a case study in an input market, Uber’s “Hell” program. This exposition highlights the technical possibilities for more targeted pricing and other forms of algorithmic targeting in the future and sets out the basis for reconsidering the analysis of predation pricing, rebates, and tying and

5. *Huge “Foundation Models” Are Turbo-Charging AI Progress*, THE ECONOMIST (June 11, 2022), <https://www.economist.com/interactive/briefing/2022/06/11/huge-foundat-ion-models-are-turbo-charging-ai-progress> [https://perma.cc/M3E3-7CXS].

6. *Id.*

7. *Id.*

8. *Id.*

bundling in the world of algorithms. Subsequently, we explore in greater detail how the fundamental assumptions underlying the traditional doctrines on predatory pricing, rebates, and tying and bundling may be challenged by algorithmic targeting and what changes may be necessary to adapt these doctrines to the new technological reality.

We argue that the possible incorporation of algorithmic targeting in the future in the implementation of predatory pricing, anticompetitive targeted rebates, and tying would pose much greater challenges to antitrust analysis of such conduct than is currently understood. This article argues that the possibility of algorithmic targeting would render recoupment much more feasible. It would significantly reduce the importance of the recoupment requirement, perhaps to the extent of redundancy in a number of cases. This article also puts forward the argument that the targeted implementation of ties would minimize the profit tradeoff facing a tying firm and would reduce the minimum amount of market power necessary to implement a profitable tie. This may require a fundamental rethink of the current legal standards as they are applied to algorithmic predation and exclusion.

Some may accuse us of being speculative or perhaps even scaremongering. It is unclear whether big data and algorithms have such capabilities now or will acquire them in the foreseeable future. And, while algorithms may not currently have the full capability to segment customers precisely—although there is evidence that they already possess some capability to do that from Uber’s Hell program—events in the last few years have illustrated the importance for competition law to look ahead and anticipate technological changes. The response of competition law to Big Tech has been one of constant catch-up. If competition law only starts to deliberate and formulate its response after a new technology has emerged, it will often be too late. We believe that it is the job of academics to think ahead so that both the legal doctrines and the enforcement authorities can future-proof and are able to react promptly once the challenges posed by new technology materialize.

II. ALGORITHMIC TARGETING AND NEW FRONTIERS OF PREDATORY AND EXCLUSIONARY CONDUCT

In this section, we show how the combination of algorithms with big data allows companies, such as Uber, to personalize their offers and how this might give rise to algorithmic targeting and exclusion. The first part of this section uses the case study of Uber’s Hell program to show how big data and algorithms can be used to identify and target drivers who multi-home and drive for a competitor. Uber can react to this competitive threat accordingly

by directing more rides to these drivers and offering special bonuses. In the second part, this section applies insights from the Hell case study to explore the impact that algorithmic targeting may have on other forms of exclusionary behavior.

A. An Upstream Case Study: Hell—Predation and Rebates at Work and the Feasibility of Personalized Pricing

An example that illustrates the potential of using algorithms to target efforts to exclude competitors from input can be found in the case of Uber's Hell program.⁹ Hell was a program run by Uber to target drivers that also drove for a competitor. The program had three components: (1) the collection and combination of data, (2) the identification of drivers who were also driving for competitors, and (3) targeted incentives for these drivers.

Initially, information was collected on the availability in an area of drivers who offered their services via a competitor. It is worth noting that this collection was most likely illegal in some jurisdictions.¹⁰ The data were then combined with the data of drivers who offered their services via Uber in the same area and time frame. The combination of these two data sets collected over a longer period allowed Uber to use an algorithm to identify those drivers who also offered their services via a competitor. In the final step, these “multi-homing” drivers were targeted and treated differently from other drivers. To entice them to drive for Uber exclusively, these drivers would receive more offers to pick up passengers and would be given special bonuses if a certain number of rides per week were met.¹¹ One could also

9. See Ignacio Herrera Anchustegui & Julian Nowag, *Buyer Power in the Big Data and Algorithm Driven World: The Uber & Lyft Example*, COMPETITION POL'Y INT'L, Sept. 2017, at 2–4, <https://www.competitionpolicyinternational.com/wp-content/uploads/2017/09/CPI-Anchustegui-Nowag.pdf> [<https://perma.cc/KQM9-EWYS>].

10. In many EU jurisdictions, it would have run into problems with the data protection laws, or it would be at least contrary to the terms and conditions of the competitor's app where the data was collected from. It would, for example, be in contravention of the EU General Data Protection Regulation (GDPR), 2016 O.J. (L 119), and in particular the obligation to collect data in a transparent manner to the data subject and that data collected is processed only for specific purposes and not in manner that is incompatible with the original purposes, *see id.* at 35–36. Uber apparently did not inform the drivers that it would collect data from the Lyft app and then combine this data with data from the Uber app for the purpose of identifying multi-homers. Moreover, it also did not obtain the relevant consent. *See id.* at 36–37. Hence, it is difficult to see how such an activity could be legal under the GDPR.

11. Mariella Moon, *Uber's "Hell" Program Tracked and Targeted Lyft Drivers*, ENGADGET (April 13, 2017, 3:32 AM), <https://www.engadget.com/2017/04/13/uber-hell-program-lyft-drivers> [<https://perma.cc/P4YP-T9X6>].

imagine that better prices were offered to these drivers.¹² All this happened without the drivers knowing that they were accorded more favorable treatment because they were also offering their services on a competing platform.

What makes the case of Uber's Hell program an interesting case study and exemplary for our purpose is the use of big data and algorithms to provide rebates or bonuses. These were, however, only available to those drivers who could multi-home. In this sense, Uber's Hell program can be said to be aimed at allowing Uber to exclude a competitor from the input market. The tools were very targeted. They included personalized rebates, bonuses, or personalized overbuying.¹³ There are not many (legal) countermeasures that the competitor could undertake that would not increase its costs: (1) pay a higher price to the existing drivers (through higher bonuses or by reducing the fees), (2) introduce exclusivity clauses in the driver contract, or (3) recruit more drivers.¹⁴ In the first case, the increase in cost is obvious. In the second case, one could expect drivers to demand a premium for exclusivity, whether monetary or otherwise. There would also be monitoring costs involved to ensure compliance with the exclusivity clause. The third option could also incur greater costs as marginal drivers may need to be attracted by higher pay, improved benefits, or higher marketing expenditure.

Two things are noteworthy in this context. First, these costs could be substantial, as they would be incurred across the board with all drivers. Only where the competitor has a similar capacity to personalize its rebates could the cost increase be contained. This seems to stem from the fact that Uber is able to target only the marginal drivers. Without algorithmic schemes that facilitate such targeting, the competitor would have to offer higher pay to all drivers. Second, it makes sense for Uber to steal as many drivers from its competitor as possible because it reduces the attractiveness of the competitor downstream.¹⁵ The Hell program seems to have allowed Uber to steer its demand for drivers in such a way that it would hurt its competitors at the same time.

The use of big data and algorithms allowed Uber to distinguish between those drivers that might multi-home from those who only driver for Uber. In

12. In the case of Uber, this is done by lowering the fee that Uber charges the drivers.

13. For more details on these theories in the context of the Hell program, see *generally* ANCHUSTEGUI & NOWAG, *supra* note 9.

14. Leaving aside the possibility that the competitor could have mirrored the behavior of Uber and collected the data from the Uber app illegally.

15. Waiting time is the essential feature of the perceived quality of a ride hailing platform, which in turn is determined by the available number of drivers.

a sense, multi-homers are a great proxy for marginal drivers, as only multi-homing drivers are likely to drive for competitors. In this way, Uber did not have to offer the incentives in the form of bonuses to all drivers and could thereby reduce the overall costs for incentivizing the drivers to stay loyal to Uber. Consequently, any profit required in the recoupment of the costs of such a bonus program would also be correspondingly smaller. Moreover, the smaller number of drivers involved would allow Uber to offer higher bonuses than if bonuses were offered across the board.

Although the case study of Uber's Hell program shows the potential to target the marginal *input* of a competitor *upstream*, such exclusion might equally occur *downstream*. The prime candidates that would be in a position to amass enough data for such targeting are Amazon and other large retailers with sufficient data inputs.¹⁶ These firms are able to collect vast amounts of data on spending patterns and sales of their own brand products as well as competing products. In fact, Amazon has been caught price discriminating against different customers based on their browsing history over the sale of DVDs and mahjong tiles.¹⁷ It has also supplied personalization technology to third-party sellers on its platform. An empirical analysis by Le Chen, Alan Mislove, and Christo Wilson details the prevalence of algorithmic pricing in Amazon Marketplace and finds that algorithmic sellers are much more active there and are more successful.¹⁸ Chen et al. also find 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.¹⁹

Hotel booking websites are also known for making use of demographic data to engage in price discrimination.²⁰ Even Home Depot has reportedly been found to price discriminate.²¹ Google might at some point also have sufficient data to provide targeting services to third parties similar to its targeted advertising, given that it collects spending patterns online and

16. There is already a debate as to whether Amazon has engaged in predation. See Shaoul Sussman, *Prime Predator: Amazon and the Rationale of Below Average Variable Cost Pricing Strategies Among Negative-Cash Flow Firms*, 7 J. ANTITRUST ENF'T 203, 203–19 (2019).

17. Axel Gautier, Ashwin Ittoo & Pieter Van Cleynenbreugel, *AI Algorithms, Price Discrimination and Collusion: A Technological, Economic and Legal Perspective*, 50 EURO. J.L. & ECON. 405, 408–09 (2020).

18. 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).

19. *Id.* at 1347–48.

20. Gautier et al., *supra* note 17, at 410.

21. *Id.*

offline via Gmail accounts, for example.²² Such targeting services would most likely be provided to companies selling to the final consumer. However, it is also possible to imagine similar targeting services further upstream in the supply chain targeting downstream competitors.

Aside from these real-world examples, the feasibility of more targeted pricing by algorithms using sophisticated machine learning has been demonstrated in a number of experimental studies.²³ A number of commentators, such as Salil Mehra and Michal Gal, have noted the enhanced ability of algorithms to engage in price discrimination.²⁴ A report by the Obama Administration highlighted the possible consumer harm that may flow from more precise price discrimination.²⁵ The OCED has also acknowledged the possibility of individualized pricing by algorithms and warned about the competitive implications of such practice.²⁶ The CEO of Safeway, an American supermarket chain, asserted 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.”²⁷

This is not to say that personalized pricing is already a regular occurrence. Some commentators have argued that it remains a theoretical possibility rather than a reality.²⁸ Gal has argued that businesses could be deterred by consumer backlash and thwarted by consumer countermeasures in the pursuit of personalized pricing.²⁹ Therefore, technical feasibility would not necessarily translate into real-life practices. There are reasons, however, to doubt the extent to which consumer backlash will provide adequate deterrence.³⁰ There has been significant consumer discontent with the data collection policy of the Big Tech firms such as Facebook. The public outcry has so far failed to produce fundamental changes to their data collection

22. See Todd Haselton & Megan Graham, *Google Uses Gmail to Track a History of Things You Buy—And it’s Hard to Delete*, CNBC (May 17, 2019, 2:09 PM EDT), <https://www.cnbc.com/2019/05/17/google-gmail-tracks-purchase-history-how-to-delete-it.html> [https://perma.cc/6ZWH-WD2M].

23. Gaultier et al., *supra* note 17, at 415.

24. Salil K. Mehra, *Price Discrimination-Driven Algorithmic Collusion: Platforms for Durable Cartels*, 26 STANFORD J.L., BUS. & FIN. 171, 175 (2021); Gal, *supra* note 3, at 91.

25. Mehra, *supra* note 24, at 180.

26. OECD, ALGORITHMS AND COLLUSION: COMPETITION POLICY IN THE DIGITAL AGE 16 (2017), <https://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm> [https://perma.cc/SH9S-UG5R].

27. Terrell McSweeney & Brian O’Dea, *The Implications of Algorithmic Pricing for Coordinated Effects Analysis and Price Discrimination Markets in Antitrust Enforcement*, 32 ANTITRUST, Fall 2017, at 75, 77.

28. Gaultier et al., *supra* note 17, at 415.

29. Gal, *supra* note 3, at 92.

30. See in this regard also Leslie, *supra* note 1.

privacy.

All in all, personalized pricing is thus far more likely to be a theoretical possibility than a reality.³¹ The kind of price discrimination that has been implemented by Amazon and the hotel booking websites so far is much cruder than the kind of first-degree price discrimination needed for personalized pricing. Uber's Hell program may indicate the technological possibility in the future, although finding out whether your driver also drives for a competitor is admittedly considerably easier than identifying whether a customer is marginal or inframarginal or assessing an individual customer's willingness to pay. Regardless of the capability of different algorithms, the availability of data and the ability to process raw data put a limit on the feasibility of personalized pricing.³² However, with the increasing amount of data available and collected, the increasing processing power of computers, and the growing capabilities of AI such as foundation models, the boundaries set by these limitations are constantly shifting. What we can confidently say at this point is that some form of price discrimination is already feasible and being implemented, and that it is entirely possible that algorithms may acquire the capability to segment customers precisely as marginal and inframarginal in the not-too-distant future. Whether truly personalized pricing will be attainable is more speculative. The discussion that follows, however, is not premised on personalized pricing. What is merely required is more precise customer segmentation. It would be a folly to attempt to predict the direction of future technological development. But history has also taught us that it would be equally presumptuous for us to rule anything out, especially when the gap between current technological capability and the eventual destination is not distant and insurmountable. The remainder of this article will proceed on the basis that, while truly personalized pricing is not feasible at the moment, more precise customer segmentation that could fundamentally change how antitrust approaches and analyzes a range of competitive conduct could be eminently attainable in the future, if not already in existence. The antitrust community should start to pay attention to this possibility now so that it will not be caught flat-footed when the day eventually arrives.

31. Although some claim that certain forms for personalized pricing based on the willingness to pay are already possible, see Mehra, *supra* note 24, at 175, others claim that "there is no strong evidence showing that firms are actually implementing finer-grained" price discrimination, Gaultier et al., *supra* note 17, at 415. Gaultier et al., however, acknowledge the "huge potential for [price discrimination] based on AI algorithms and data." *Id.* at 411.

32. See Gaultier et al., *supra* note 17, at 421; OECD, *supra* note 26, at 9.

B. Other Forms of Targeted Exclusionary Conduct

Some form of price discrimination is already happening. Even if the ability to engage in truly personalized pricing remains elusive at this point, technological progress may turn more precise customer segmentation into a reality in the future. As mentioned earlier, the analysis and conclusions offered in this article are not premised on personalized pricing. The ability to distinguish marginal from inframarginal customers, which we call algorithmic targeting and is much less technically demanding, would suffice. In the ensuing discussion, we briefly look at the possible effects of algorithmic targeting for a range of exclusionary conduct and their applicable legal tests.

1. Predatory Pricing

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. More targeted price cuts would help the predating firm to minimize the costs of predation by obviating the need to sustain losses on sales to inframarginal customers. A smaller predation loss would mean there is less to recover during the recoupment stage, making recoupment more likely and, consequently, predatory pricing a more plausible and feasible strategy. The trans-Atlantic divergence on predatory pricing centers on the need to prove likelihood of recoupment, which is not a required element for predatory pricing under European Union (EU) law. Algorithmic targeting may necessitate a reexamination of the recoupment requirement under U.S. law and bolster the EU position in this debate.

Algorithmic targeting also has an impact on the cost measures used to determine the existence of below-cost pricing. A variety of cost measures, such as marginal cost, average variable cost, average incremental cost, and average avoidable cost, have been proposed for the purpose of determining whether prices are below cost.³³ Whether these cost measures are still appropriate in light of algorithmic targeting becomes a valid question that will also be examined in the next section.³⁴

2. Anticompetitive Targeted Rebates

As Uber's Hell program demonstrates, algorithmic targeting would also

33. *See infra* Part III.

34. *Id.*

render the use of rebates much more precise. A similar cost-based approach as used for predation can be used to analyze rebates. Rebates can occur on a standardized basis as, for example, in the EU case of *Post Danmark II*,³⁵ or an individualized basis, that is to say, a different discount for each customer, as in the EU *Intel* case.³⁶

The use of algorithms would make possible a new form of rebates. These rebates would obviate the need for individual calculations and negotiations. They would combine the benefits of both standardized and individualized rebates. Standardized rebates are easy to roll out, as they apply across the board to all customers. Yet, for some customers, the rebate rate set by the standardized rebate scheme may not be profit maximizing. What is relevant for the company is that the overall effect of the rebate is to maximize profit. Individualized rebates can alleviate that problem, as they are tailored to each client's profile. Yet, due to much higher transaction costs, it might not be profitable to operate a system of individualized rebates to a large, diverse group of customers.

Algorithmically targeted rebates would kill two birds with one stone. They would be cheaper to implement than individualized rebates but simultaneously could be implemented across large groups of customers like standardized rebates. Algorithms would improve the effectiveness of rebates by allowing for better targeting across a large group of customers. In particular, with these techniques it would be possible to identify the contestable sale unit. It would become possible to identify individual transactions over which competition exists and adjust the price accordingly. Discounts could be implemented in a much more targeted manner, making them much less costly to pursue.

3. Tying and Bundling

Tying and bundling allows a dominant firm to leverage its dominance in one market to obtain an advantage in another market where the firm does not yet have such a position.³⁷ One may distinguish between *pure* and *mixed*

35. Case C-23/14, *Post Danmark A/S v. Konkurrencerådet*, ECLI:EU:C:2015:651, ¶ 10 (May 21, 2015).

36. Case C-413/14 P, *Intel v. Comm'n*, ECLI:EU:C:2017:632, ¶ 11 (Sept. 6, 2017).

37. For landmark cases in the EU, see, for example, Case 22/78, *Hugin Kassaregister AB v. Comm'n*, 1979 E.C.R. 1869; Case T-83/91, *Tetra Pak Int'l SA v. Comm'n*, 1994 E.C.R. II-755; Case T-30/89, *Hilti AG v. Comm'n*, 1991 E.C.R. II-1439; Case T-201/04, *Microsoft Corp. v. Comm'n*, 2007 E.C.R. II-3601. For cases in the U.S., see, for example, *Eastman Kodak Co. v. Image Tech. Servs., Inc.*, 504 U.S. 451 (1992).

bundling.³⁸ A *pure bundling* case is the quintessential tie. The dominant firm makes it impossible to buy products A and B separately. The firm only sells them together as a bundle. In the case of *mixed bundling*, the customers have a choice. They can either buy products A and B separately or they can buy the A-B bundle cheaper from the dominant firm. Mixed bundling is known as “bundled discounts” in the United States.³⁹

Algorithms may also facilitate the practice of tying and bundling. They may allow a firm to identify customers based on the elasticity of their demand. This would affect the relevant trade-offs and, thereby, the profitability of tying and bundling. Tying or bundling strategies usually entail a trade-off between the loss of revenue from customers who would stop buying the tying product from the tying firm due to the tie, on the one hand, and gains from those who would stick with the tying firm’s product despite the tie, on the other hand. This trade-off determines the profitability of the strategy.⁴⁰

Algorithmic targeting would allow the tying firm to offer a tie to those locked-in customers with an inelastic demand. The inframarginal customer would be forced to buy the bundle.⁴¹ The revenue gained from the tie could then be used to offer bundled discounts to customers with an elastic demand at a price lower than that of competitors to ensure that they do not switch to a competitor. Thus, only the marginal customer would be offered the discounted bundle of AB. In fact, the discounts offered to the marginal customer could be further optimized by algorithmically targeted rebates, as explained above. This ability to differentiate customers seems to suggest that such a strategy could be successfully employed at a lower level of market power.

C. *The Core Challenges of Algorithmic Targeting*

The foregoing discussion indicates two main challenges when exploring the possible use of algorithmic targeting to provide targeted predation, rebates, and tying and bundling.

First, some of the general assumptions about these practices would need

38. ROGER VAN DEN BERGH, *COMPARATIVE COMPETITION LAW AND ECONOMICS* 316–17 (2017).

39. *Id.*

40. *Id.* at 317–18.

41. For more details and, in particular, on how a tying seller can impose tying arrangements on inframarginal consumers, see Christopher R. Leslie, *Cutting Through Tying Theory with Occam’s Razor: A Simple Explanation of Tying Arrangements*, 78 TUL. L. REV. 727, 770 (2004).

to be questioned. For example, in predation cases, it is traditionally asked how a firm can afford below-cost pricing,⁴² and whether the predation loss can be recouped.⁴³ Algorithms would allow firms to target their price cuts. Thus, only marginal customers would receive the “benefit” of below-cost pricing, whether in the form of a lower price, rebates, or a discounted bundle. Such targeting means that in-group cross-subsidization would be much more relevant. Price discrimination within a customer group would make possible predation, rebates, and mixed bundling for the marginal customers, paid for by the inframarginal customers. Below-cost pricing could be implemented without a substantial loss.

Cross-subsidization, however, would not be the only way in which algorithmic targeting could facilitate predatory and exclusionary behavior. The cost of predation and exclusionary conduct would be dramatically reduced, as the predatory price, the rebate, or the bundle would only be offered to a smaller number of customers, and only for specific transactions. This reduction in costs would completely change the cost-benefit calculation.⁴⁴ The loss that would need to be recovered would be much lower, and the time frame for recovery (if any actual loss is incurred due to the cross-subsidization) would be much shorter. Predatory or exclusionary conduct would become more profitable and, hence, more probable for a dominant undertaking.⁴⁵

Second, often neither the customers nor the competitors would be aware that algorithmic targeting is possible. This is relevant for two reasons. First, if the customer knew that they had been classified as inframarginal, they might have a chance to react. Strategic behavior on the part of the customer could change the classification of the customer or the specific transaction. In essence, this is a question of information asymmetry, but it might equally be a matter of capabilities.⁴⁶ Second, a competitor who does not engage in such

42. In other words, a question of the deep pockets of the predator and where they are derived from.

43. With regard to Amazon, see Sussman, *supra* note 16. With regard to overbuying in general, see John B. Kirkwood, *Buyer Power and Exclusionary Conduct: Should Brooke Group Set the Standards for Buyer-Induced Price Discrimination and Predatory Bidding*, 72 ANTITRUST L.J. 625 (2005); Steven C. Salop, *Anticompetitive Overbuying by Power Buyers*, 72 ANTITRUST L.J. 669 (2005); and Richard O. Zerbe, Jr., *Monopsony and The Ross-Simmons Case: A Comment on Salop and Kirkwood*, 72 ANTITRUST L.J. 717 (2005).

44. The cost of collecting and analyzing big data might be factored in. Currently these costs are being reduced rapidly. See in particular *infra* Part III.

45. ANCHUSTEGUI & NOWAG, *supra* note 9, at 4.

46. With regard to the identification of vulnerable utilities consumers, see DEP'T FOR BUS., ENERGY & INDUS. STRATEGY, CONSUMER GREEN PAPER: MODERNISING CONSUMER MARKETS 12–15 (2018), <https://assets.publishing.service.gov.uk/government/uploads/system>

targeting would be severely disadvantaged. Any counter-strategy, for example, price cutting in reaction to predatory prices, would need to be adopted on a much broader scale, entailing a much higher cost.⁴⁷

III. ALGORITHMIC TARGETING AND PREDATORY PRICING

Once it becomes a technological reality, algorithmic targeting would have the potential to revolutionize the execution of predatory and exclusionary conduct. By allowing the dominant firm to target its price cutting, rebates, or tying conduct at the marginal customers, it would dramatically lower the costs of predatory and exclusionary conduct and would fundamentally alter the cost-benefit analysis for the dominant firm. Algorithmic targeting would thus require new thinking on the prevailing legal tests for these practices. Many of the existing legal tests are premised on certain assumptions about the profitability and the modus operandi of the conduct. Once these assumptions no longer hold true, there would be room for reconsidering these legal tests. In the following sections, we examine these assumptions and tests and explore the possible impact that algorithmic targeting has on them.

One of the main implications of algorithmic targeting for predatory conduct relates to recoupment. The requirement of recoupment for establishing a predatory pricing claim does not exist under EU law, while it is mandated by the U.S. Supreme Court in the *Brooke Group* case.⁴⁸ Whether recoupment should be required for a predatory pricing claim has been the subject of a long running debate.⁴⁹ Without trying to settle the merit of this debate, this article argues that the possibility of algorithmic targeting would render recoupment much easier and more feasible, thereby significantly reducing the importance of the recoupment requirement.

A. *Recoupment: Possible Current Approaches*

A predator is deemed to have recouped its predation loss if the additional profit earned as a result of successful predation during the

/uploads/attachment_data/file/699937/modernising-consumer-markets-green-paper.pdf [https://perma.cc/V788-YK4D].

47. There might also be questions as to whether the competitor would have sufficient access to data to counter in an equally efficient manner.

48. *Brooke Grp. Ltd. v. Brown & Williamson Tobacco Corp.*, 509 U.S. 209 (1993).

49. See, e.g., Christopher R. Leslie, *Predatory Pricing and Recoupment*, 113 COLUM. L. REV. 1695 (2013); Louis Kaplow, *Recoupment and Predatory Pricing Analysis*, 10 J. LEGAL ANALYSIS 1 (2018); C. Scott Hemphill, *The Role of Recoupment in Predatory Pricing Analyses*, 53 STAN. L. REV. 1581 (2001).

recoupment period outweighs the loss it sustains from the below-cost price cuts during the predation period.⁵⁰ The most intuitive way to ascertain recoupment is, therefore, to compare the magnitude of predation losses and post-predation gains.⁵¹ Scott Hemphill calls this a “conduct-based” approach, which seeks to estimate directly the expected losses and gains from predation and compare their relative size.⁵² It can thus be called the *direct approach*. An alternative approach is the structural approach or the *indirect approach*, which eschews a direct comparison of the relative magnitude of the predation loss and the post-predation gains and focuses on structural indicators of probable post-predation profits.⁵³ The indirect approach makes no attempt to ascertain the size of the predation loss and assumes that it will be outweighed by post-predation gains if market structure renders such gains substantial and likely.⁵⁴

Thus far, the courts have not expressed a clear preference between these two approaches. *Brooke Group* arguably adopted the direct approach with respect to measurement of predation loss and the indirect structural approach to ascertaining the possibility of recoupment gains. The Court largely dismissed the plaintiff’s case on the grounds that the structural characteristics of the market rendered recoupment so implausible that the predatory pricing claim could not be substantiated.⁵⁵ In the following discussion, we explore the direct and indirect approaches and investigate how algorithmic targeting would affect their application. Due to the lack of guidance from the courts, the ensuing discussion will draw heavily on the academic literature.

1. The Direct Approach

The direct approach entails a direct comparison between the predation loss and the post-predation recoupment gains.⁵⁶ This comparison is not as straightforward as it may seem. The precise meaning of predation losses is, in fact, open to interpretation.

50. Leslie, *supra* note 49, at 1699.

51. Kaplow, *supra* note 49, at 9.

52. Hemphill, *supra* note 49, at 1590.

53. *Id.* at 1587–88 (“A structure-based recoupment screen distinguishes good and bad price cuts without examining the price cut itself. Instead, the screen assesses the structural factors that create sustained power over price, factors that provide the predator with a chance to make substantial profits after the competitor has been eliminated or co-opted.”).

54. *Id.* at 1587.

55. *Brooke Grp. Ltd.*, 509 U.S. at 239–43 (1993).

56. Hemphill, *supra* note 49, at 1590.

a. *Predation loss*

There are two possible ways to measure the predation loss, which have been described by Steven Salop as the negative profit standard and the true profit sacrifice standard.⁵⁷

Under the *negative profit standard*, the loss is simply the loss that is directly caused by the below-cost pricing. When prices are below cost, total revenue will be smaller than the costs for producing the units sold. The difference between total revenue and total costs would be the predation loss. Salop argues that this is the standard adopted by the U.S. Supreme Court in *Brooke Group*.⁵⁸

Under the *profit sacrifice standard*, the predation loss would be the difference between what the defendant would have made absent predation and its actual profit after predation.⁵⁹ Application of this standard requires a benchmark against which the loss or sacrifice of profit during the predation period is measured.⁶⁰ Salop cautions that the benchmark for comparison under this standard should not be the pre-entry monopolist price.⁶¹ Instead, “[t]he proper benchmark is the market price that would prevail if the entrant had sufficient financial resources to survive a price war (i.e., if there would be no exit for the rival and no recoupment for the predator).”⁶²

After the entrant survives the price war, the market enters into a state which Louis Kaplow calls “accommodation,” under which the former monopolist accommodates the new entrant by reducing his output and cuts his prices in light of the now-expanded market output.⁶³ In Kaplow’s formulation of the recoupment requirement, the predation loss is calculated by comparing the defendant’s profit in the state of accommodation with his profit under predation.⁶⁴ The predation loss is then compared with the post-predation gains, which are in turn calculated by comparing the defendant’s

57. Steven C. Salop, *Exclusionary Conduct, Effect on Consumers, and the Flawed Profit-Sacrifice Standard*, 73 ANTITRUST L.J. 311, 326 (2006).

58. *Id.* See also Hemphill, *supra* note 49 at 1590–91 (“[T]he *Brooke Group* opinion seems to suggest a simple, conduct-based recoupment test. In the simplest formulation of conduct-based recoupment, a court could calculate the incumbent’s losses from predation, and calculate (likely) gains after predation has ended, and compare the two to see which is larger. (Equivalently, a court could compare losses and gains to see whether the total is positive or negative.)”).

59. Salop, *supra* note 57, at 326–28.

60. *Id.* at 326.

61. *Id.* at 327.

62. *Id.*

63. Kaplow, *supra* note 49, at 9.

64. *Id.*

post-predation monopolist profit with his profit under accommodation.⁶⁵

These two standards produce different results for the predation loss, with the negative profit standard being more beneficial for the plaintiff and the profit sacrifice standard being more beneficial for the defendant.⁶⁶ The predation loss calculated under the negative profit standard is typically lower than that under the profit sacrifice standard. Under the negative profit standard, only the actual loss incurred by the defendant will be considered as part of the predation loss.⁶⁷ Under the profit sacrifice standard, profit that the defendant would have made in a state of accommodation will also be included.⁶⁸ The resulting larger profit sacrifice should make it, all else equal, more difficult for the plaintiff to demonstrate successful recoupment.⁶⁹ The extent to which this is true will depend on how the post-predation gains are calculated.

b. Post-predation gains

The post-predation gains are the mirror image of the predation loss. Therefore, logic dictates that there are also two ways to calculate them. The first would be the *true profit standard*, which measures the size of the overall profit for the defendant post-predation. The second would be the *incremental profit standard*, which calculates the additional profit the defendant made by engaging in predation as opposed to accommodating new entry.⁷⁰ The results for post-predation gains under these two standards are the reverse of those for the predation loss. The true profit standard should produce a larger gain than the incremental profit gain standard because the former would include the profit the defendant would have made under accommodation as part of the gain.

The profit sacrifice standard combined with its corresponding incremental profit standard (collectively called the *hypothetical profit standards*) are probably sounder. The defendant's predation loss and post-predation gain should be compared with their profit and loss if predation had never happened after the incumbent has accommodated new entry.⁷¹ The difficulty with the hypothetical profit standards is that it requires an estimation of the predator's profit in the but-for world, which is far from

65. *Id.*

66. Salop, *supra* note 57, at 326.

67. *Id.* at 314–15.

68. *Id.* at 327–28.

69. Kaplow, *supra* note 49, at 9.

70. Salop, *supra* note 57, at 324.

71. Hemphill, *supra* note 49, at 1596.

easy.⁷² The ease with which the negative profit standard with its corresponding true profit standard (collectively the *actual profit standards*) can be applied depends on whether recoupment has already taken place. These standards should be relatively easier to administer if recoupment has already taken place, as the actual profit and loss for the predator can be readily ascertained. In contrast, estimation of post-predation gains would require guesswork on the part of the courts if the case were brought before the recoupment phase has started.⁷³

Theoretical soundness needs to be balanced against practicality in choosing between these two sets of standards. The choice of standard, however, probably matters less than the consistency of the choices. So long as the same set of standards is applied, such that the profit sacrifice standard is coupled with the incremental profit standard and the negative profit standard with the true profit standard, the comparison between profits and losses should remain valid. This would be true unless there were systemic biases in the fluctuation of accommodation profits pre- and post-predation, given that the main difference between these two sets of standards is the inclusion or exclusion of accommodation profits. There do not seem to be obvious reasons to expect such biases.

If the two sets of standards do not produce dramatically different results, the choice between them may come down to administrability. As mentioned earlier, Kaplow espouses the hypothetical profit standards.⁷⁴ Hemphill, however, rightly argues that it is very difficult to estimate the likely profits in a counterfactual scenario where predation did not occur.⁷⁵ Quantitative application of the hypothetical profit standards would likely run into significant practical difficulties. Administrability would suggest that the actual profit standards are more feasible.

The case law seems to have expressed a preference for the actual profit standards. *Brooke Group* has implicitly adopted the negative profit standard for measuring predation loss.⁷⁶ The Supreme Court, however, did not seem to have attempted to measure the post-predation gains directly but instead relied on the indirect approach to determine the feasibility of recoupment. Thus, it cannot be said that the Court has adopted the actual profit standards wholesale. Instead, it adopted more of a hybrid approach. In *United States v. AMR Corp.*, the Tenth Circuit also seems to have implicitly endorsed the actual profit standards by refusing to consider profit sacrifice as part of the

72. *Id.* at 1597.

73. *Id.*

74. Kaplow, *supra* note 49, at 11–12.

75. Hemphill, *supra* note 49, at 1597.

76. Salop, *supra* note 57, at 326.

predation cost.⁷⁷ The Tenth Circuit, however, did not directly repudiate the hypothetical profit standards. The cost measure that it rejected as “Test One” in that case was the kind of direct “before-and-after” comparison Salop cautioned against, and not the profit that the monopolist would have made had it accommodated market entry.⁷⁸ What was being compared against was the profit made by the monopolist prior to predation as opposed to what the monopolist would have made had it accommodated market entry. Therefore, one possible interpretation is that the Tenth Circuit’s decision represented the rejection of a wrongly applied hypothetical profit standards and that it has expressed no views on the applicability of the standards if they were correctly applied.

2. The Indirect Approach

The direct approach seeks to estimate directly and compare the expected losses and gains from predation. An alternative structural,⁷⁹ or indirect, approach seems to be more commonly applied by the U.S. courts.⁸⁰ Instead of directly measuring predation gains and losses, this approach focuses on proxy indicators of likelihood of substantial post-predation gains such as high entry barriers and existing competitors’ limited capacity.⁸¹

When entry barriers are high, post-predation entry is improbable and it is unlikely that a post-predation price increase would be frustrated by competitors.⁸² Likewise, limited capacity suggests that even if existing competitors manage to outlast the predation, they are unlikely to be able to defeat a post-predation price increase through capacity expansion.⁸³ Under the indirect approach, the focus seems to be on the likelihood of substantial post-predation profit rather than on the relative magnitude of the predation loss and post-predation gain.⁸⁴ In a way, the predation loss is taken as a given and the analysis centers on the probability that the defendant will make a substantial recovery post-predation. There is no attempt to directly measure the size of the post-predation gains. Instead, the focus is on structural factors that indicate likelihood of substantial recovery.

The structural or indirect approach is a much cruder way to ascertain

77. *United States v. AMR Corp.*, 335 F.3d 1109, 1119 (10th Cir. 2003).

78. *Id.*

79. Hemphill, *supra* note 49, at 1599.

80. *Brooke Grp. Ltd.*, 509 U.S. at 239–43.

81. Hemphill, *supra* note 49, at 1587.

82. Leslie, *supra* note 49, at 1714.

83. Hemphill, *supra* note 49, at 1587.

84. *Id.*

recoupment. It makes no attempt to measure the size of the predation loss and the post-predation gain.⁸⁵ It only looks at structural proxies for substantial post-predation recovery. It has a much lower informational requirement than either standard under the direct approach. The direct approach would in most cases require some estimation of hypothetical situations. That would surely be the case under the hypothetical profit standards. But even under the actual profit standards, examination of hypotheticals might be required where the case is filed before recoupment is accomplished. Thus, while the direct approach entails an analysis of but-for scenarios, the kind of market structure analysis required under the indirect approach is the bread and butter of antitrust law.

One can argue that, at least for predatory pricing claims filed prior to successful recoupment, the indirect approach would seem to be the only feasible one.⁸⁶ This approach also has the added benefit of avoiding the perverse scenario described by Hemphill whereby deeper price cuts, which are more likely to drive out competitors and hence have a higher exclusionary potential, are likely to receive more lenient treatment under recoupment analysis since steeper losses are, all else equal, more difficult to recoup.⁸⁷

B. Algorithmic Targeting and Recoupment

Having surveyed the traditional standards for ascertaining the likelihood of recoupment, this section turns to explore the possible impact of algorithmic targeting on the analysis of predatory pricing. It first explores the general impact and then focuses on the specific impact on the direct and the indirect approaches.

1. General Impact

The possibility of algorithmic targeting would change the practice and analysis of predatory pricing in fundamental ways. In a market where the dominant firm is unable to practice price discrimination, the firm minded to predate will need to change the price for all customers if it decides to cut prices in response to market entry.⁸⁸ In that case, the determination of the

85. Frank H. Easterbrook, *Predatory Strategies and Counterstrategies*, 48 U. CHI. L. REV. 263, 269–70 (1981).

86. Hemphill, *supra* note 49, at 1597.

87. *Id.* at 1593.

88. Einer Elhauge, *Why Above-Cost Price Cuts to Drive Out Entrants Are Not*

size of the predation loss is relatively straightforward. It only entails a comparison between the market price and the average variable cost (assuming this is the correct cost measure, which will be discussed later) to determine the per unit loss. Only a single price-cost comparison needs to be undertaken because there is only one prevailing market price. The total loss at any given point in time can be calculated by multiplying the per unit loss with the total output level. The total loss during the predation period can be calculated by adding up all the losses sustained during the entire predation period.

Algorithmic targeting would allow the dominant firm to respond to competitive threats in a selective manner when these threats emerge at the downstream customer and final consumer level. Selective price cuts have always been feasible upstream at the level of wholesaler or retailers, even in the pre-digital age. Algorithms were not needed to allow a manufacturer to price discriminate against wholesalers or retailers. Yet, even if such price discrimination was possible previously, it involved transaction costs. And the level of discrimination was proportional to the costs involved. The higher the level of discrimination, the greater the transaction costs incurred. Algorithmic price discrimination changes this calculus. Price discrimination becomes easier and cheaper. In fact, the costs are disassociated from the individual transaction. Instead, a single investment in the algorithm and big data collection replaces the costs of negotiating the individual price. One might even say that the transaction costs become a fixed cost. The impact of algorithmic targeting is even more pronounced with regard to price discrimination against final consumers. The ability to do so was much more limited in the past. This is where algorithms could make a significant difference in the future.

Overall, algorithms may allow the dominant firm to differentiate between marginal customers and inframarginal customers.⁸⁹ The former are more likely to be enticed by the new entrant's product or lower prices.⁹⁰ These customers are the ones whose patronage the dominant firm will need to defend. The potential ability to distinguish between marginal and inframarginal customers and to offer different prices to them would mean that the dominant firm can make much more targeted responses in reaction

Predatory—and the Implications for Defining Costs and Market Power, 112 YALE L.J. 681, 729–30 (2003).

89. COMPETITION & MKTS. AUTH., ALGORITHMS: HOW THEY CAN REDUCE COMPETITION AND HARM CONSUMERS 9 (2021), https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/954331/Algorithms_++.pdf [<https://perma.cc/42HG9WKT>] [hereinafter ALGORITHMS].

90. *Id.*

to competitive threats. Instead of cutting prices across the board, it would only need to do so for the marginal customers.⁹¹ It could maintain its previous profit-maximizing price for the inframarginal ones.⁹² This would allow the firm to minimize the loss it must sustain from below-cost price cutting. Algorithmic targeting may allow the dominant firm to practice more targeted predatory pricing while keeping the attendant loss to a minimum. Moreover, this reduction may also shorten the length during which predatory prices must be maintained in order to inflict harm on competitors.

Algorithmic targeting would affect both predation and recoupment. Although a price increase across the board remains a possibility, it is no longer a necessity with algorithmic targeting. The firm may be able to focus the price increase on the inframarginal customers who are willing to stomach higher prices and will not be easily enticed to defect by a competitor's lower prices.⁹³ This has the advantage of minimizing the risks of inducing market entry or capacity expansion by existing competitors. This is especially likely if algorithmic targeting would reduce the number of customers potentially available to a new entrant, thereby depriving the entrant of the economies of scale that may be needed to make entry viable.⁹⁴ Thus, algorithmic targeting may allow the dominant firm to maximize its post-predation recovery while minimizing the risks of market entry, which could undermine successful recoupment. The probability of successful recoupment and predatory pricing overall is much enhanced.

At this point, critics may question the above logic by arguing that if the inframarginal customers were susceptible to price discrimination prior to predation, the dominant firm should already have imposed unfavorable prices on them. The fact of predation should make no difference. This argument overlooks the fact that the elimination of competitors following predation will further enhance the dominant firm's market power and ability to price discriminate.⁹⁵ One explanation for this is network effects, where consumer valuation of the product or service heightens as the user base grows. By eliminating competitors and capturing their customers, the dominant firm will expand its own customer base. It may do so to such an extent that network effects are reinforced, and existing customers find the product or service even more indispensable. Existing inframarginal

91. *Id.*

92. *Id.*

93. *Id.*

94. OECD, PREDATORY PRICING 7 (1989), <https://www.oecd.org/competition/abuse/2375661.pdf> [<https://perma.cc/TDA6-EZFY>].

95. Patrick Bolton, Joseph F. Brodley & Michael H. Riordan, *Predatory Pricing: Strategic Theory and Legal Policy*, 88 GEO. L.J. 2239, 2242 (2000).

customers may become even less price-sensitive, which would allow the dominant firm to raise prices further. Previously marginal customers may cease to be so, which may render them susceptible to targeted price increases. Therefore, the possibility of algorithmic targeting should improve a dominant firm's ability to recoup its predation losses.

Overall, algorithmic targeting would allow a dominant firm to minimize its predation loss and to maximize recoupment without incurring substantial risks of market entry or capacity expansion by existing competitors. This means that the predation loss that would need to be recouped would be smaller and the ease of recoupment would be higher. The probability of successful recoupment would be much improved and predatory pricing may no longer be as implausible as the U.S. Supreme Court argued in *Matsushita*⁹⁶ and *Brooke Group*.⁹⁷ The important question is how the possibility of algorithmic targeting would affect the analysis of recoupment under either the direct or the indirect approach.

2. Impact on the Indirect Approach

The answer would probably be more straightforward with respect to the indirect approach. As mentioned earlier, the predation loss is largely taken as given. The focus of this approach are the structural factors that may facilitate recoupment. Although this point is hardly ever explicitly articulated, it would seem that this structural approach would only make sense under a certain assumption about the likely magnitude of predation loss. The amount of post-predation gain needed to make up for the predation loss is dependent on the expected size of the loss. Thus, if the loss is assumed to be large, post-predation market conditions must be highly conducive to monopolistic pricing over a sustained period of time to allow full recoupment.⁹⁸ If, in contrast, the loss is presumed to be small, post-predation market conditions need not be as favorable. Recoupment may still be possible even with some small-scale capacity expansion or market entry.

The implication is that if the predation loss is expected to be smaller, perhaps considerably so, due to the dominant firm's ability to predate through algorithmic targeting, the post-predation gain needed for recoupment would also be correspondingly smaller. This means that successful recoupment may no longer require highly favorable market conditions. The structural analysis under the indirect approach may be

96. *Matsushita Elec. Indus. Co. v. Zenith Radio Corp.*, 475 U.S. 574 (1986).

97. *Brooke Grp. Ltd.*, 509 U.S. 209.

98. Hemphill, *supra* note 49, at 1592–93.

satisfied under a lower threshold. The plaintiff would no longer be required to demonstrate very high or even insurmountable entry barriers, or severe constraints on capacity expansion post-predation.

It may be worth questioning whether the kind of structural analysis that has been undertaken by the courts is still adequate in light of the advancement of technology. Structural factors would no longer fully encapsulate a dominant firm's ability to impose monopolistic prices to recoup losses.⁹⁹ While these factors may remain relevant, one of the key considerations in a world of algorithmic targeting would be the firm's ability to implement such targeting effectively. Only where the firm is unable to impose algorithmic targeting, or can only do so ineffectively, would it be forced to raise prices across the board to recoup losses.¹⁰⁰ This would inevitably result in the defection of some marginal customers.¹⁰¹ The capacity to implement algorithmic targeting would affect a firm's ability to recoup losses even under the same structural conditions. If a firm is able to implement algorithmic targeting effectively, it may be able to recoup its predation loss even under unfavorable market conditions.

Conversely, the competitors' ability to practice algorithmic targeting also needs to be considered. Although it used to be said that the ability to price discriminate is premised on market power,¹⁰² that may no longer be true with the emergence of algorithmic targeting.¹⁰³ The focus shifts. Even a new entrant or a small competitor of the dominant firm may be able to implement algorithmic targeting to varying extents. What seems relevant is the new entrant's or the small competitor's ability to implement algorithmic targeting, which in turn depends on their access to big data. Effective algorithmic targeting would be unfeasible without access to adequate data.

Where data access is sufficient, algorithmic targeting would allow the new entrant to offer different prices to the dominant firm's existing customers to entice them to defect.¹⁰⁴ For the dominant firm's marginal

99. Leslie, *supra* note 49, at 1714–17.

100. A firm can also implement price discrimination without resorting to algorithms, for example, by relying on metered tying arrangements. See Christopher R. Leslie, *Patent Tying, Price Discrimination, And Innovation*, 77 ANTITRUST L.J. 811 (2011). The discussion here is confined to situations where only direct price discrimination is feasible and other measures such as metered tying arrangements are not, perhaps because the product at issue is not used with a complementary product.

101. ROGER J. VAN DEN BERGH & PETER D. CAMESASCA, *EUROPEAN COMPETITION LAW AND ECONOMICS: A COMPARATIVE PERSPECTIVE* 93 (2001).

102. LAWRENCE A. SULLIVAN, WARREN S. GRIMES & CHRISTOPHER L. SAGERS, *THE LAW OF ANTITRUST: AN INTEGRATED HANDBOOK* 61 (3d ed. 2016).

103. Oren Bar-Gill, *Algorithmic Price Discrimination When Demand Is a Function of Both Preferences and (Mis)perceptions*, 88 U. CHI. L. REV. 217, 225–27 (2019).

104. *Id.* at 225–26.

customers, the entrant can offer competitive, but not necessarily the lowest, prices. For the inframarginal customers, the entrant may need to offer yet lower prices. Because the dominant firm's ability to recoup losses is now highly dependent on its ability to extract substantial consumer surplus from the inframarginal customers, the entrant's ability to offer targeted prices to these customers may significantly undermine the dominant firm's recoupment. The dominant firm's inframarginal customers are now more vulnerable to a new entrant's overtures because algorithmic targeting would allow the entrant to enhance the attractiveness of its competitive offering to entice these customers. Therefore, while algorithmic targeting would strengthen a dominant firm's ability to predate and recoup, it would also allow a new entrant to tailor its competitive responses and target the dominant firm's customers effectively. A structural analysis under the indirect approach would be incomplete without regard to other firms' ability to implement algorithmic targeting as well.

3. Impact on the Direct Approach

The implications of algorithmic targeting for the direct approach requires a more elaborate explanation. It would seem that with algorithmic targeting, the choice between the hypothetical profit standards and the actual profit standards is no longer a matter of administrative convenience but will have substantive effects on the outcome of the analysis. This can be illustrated with a numerical example. Assume the market output level is one hundred units of a product. The average variable cost of producing the product is \$50, and the average market price of the product for all customers (an average is used here because of algorithmic targeting) prior to the launch of predation is \$100. Further assume that each customer buys one unit of the product and that, of the one hundred customers, seventy are inframarginal and thirty are marginal. In response to market entry, the predating firm lowers the price for the marginal customers to an average price of \$20, while the price for the inframarginal customers remains the same. In this situation, the actual profit standards produce a different result from that under the hypothetical profit standards.

a. Actual profit standards

Under the actual profit standards, it is clear that situations exist where the dominant firm would not suffer a loss after engaging in algorithmic predation. Assuming no fixed costs for the moment, it would make a profit of \$3,500 from the inframarginal customers while incurring a loss of \$900

from the marginal customers. It would still make a \$2,600 profit overall. It would seem that, so long as the inframarginal customers significantly outnumber the marginal ones and/or the profit margin for each inframarginal customer substantially outweighs the loss for each marginal customer, the dominant firm would continue to make a positive profit despite engaging in predatory pricing. The existence of a positive predation profit of course would mean that there is no loss to recoup under the actual profit standards, and therefore no valid predatory pricing claim.

b. Hypothetical profit standards

The outcome would be different under hypothetical profit standards. As explained above, these tests compare the dominant firm's hypothetical profit in the state of oligopolistic accommodation with its profit under predation. Assume that the average price for the product in a state of oligopolistic accommodation is \$85, and the dominant firm's output is reduced to eighty units. Its profit in this hypothetical accommodation state would be \$2,800. Compare this to the dominant firm's actual profit of \$2,600 in the state of predation. The firm would have thus sacrificed profit by engaging in predation and would therefore have lost profit that it needs to recoup post-predation. The predatory pricing claim at least would not be dismissed out of hand. The possibility of a profit sacrifice would remain significant, even in the presence of algorithmic targeting.

c. Options for adjustments

The choice of profit standards would actually matter in the world of algorithmic targeting in the future, and the choice can no longer be made simply based on administrative convenience. The two sets of standards no longer produce the same results. If antitrust law is to continue to take predatory pricing seriously, it seems that some adjustments would need to be made to the application of the recoupment requirement. Possible adjustments include abandonment of the actual profit standards, a refinement of the application of the actual profit standards, or the abandonment of the recoupment requirement altogether.

i. Abandonment of the actual profit standards

The first possible adjustment is the abandonment of the actual profit standards in favor of the hypothetical profit standards, which, as argued earlier, are theoretically sounder. One may argue that the continual

application of the actual profit standards would effectively eliminate predatory pricing as an antitrust violation, which perhaps was what the Supreme Court intended in *Brooke Group*. Detractors may retort that this overstates the likely impact of algorithmic targeting, and it is possible that a dominant firm would still make a negative profit from below-cost pricing, even if such price cuts were highly selective. For that to be the case, however, the group of marginal customers would need to be sufficiently large. Even if the profit margin for each inframarginal customer and the loss for each marginal customer were equal in magnitude, the two groups of customers would need to be of the same size. For a dominant firm operating in a market with a differentiated product, and possibly commanding significant brand loyalty, it would take a highly effective entrant to be able to turn half of the dominant firm's existing clientele into potential customers.¹⁰⁵ In most cases, the dominant firm should be able to respond effectively to entry with selective price cuts without incurring an overall loss. But this does not mean that such predatory behavior should be overlooked by antitrust enforcers. Given that, as Hemphill noted, the hypothetical profit standards are highly challenging to apply in practice, it would seem that some adjustments to the actual profit standards would be necessary if they were to be retained.

ii. Adjusting the actual profit standards

If the actual profit standards were to be applied in a meaningful manner, one possible adjustment would be to apply a narrower market definition. The sub-markets for marginal customers and inframarginal customers could be distinguished.¹⁰⁶ This is in fact not an uncommon practice in merger review cases where sub-markets are defined for different groups of customers when price discrimination is possible.¹⁰⁷ If below-cost price cuts are only applied to the marginal customers, the relevant sub-market will be defined to include only them.¹⁰⁸ This would prevent predation loss from being diluted by the profits from the inframarginal customers.¹⁰⁹ In some ways, such market definition would be tantamount to defining temporal markets for the predation period and the recoupment period, as the monopolist's action is likely to affect only the marginal customers during the predation period and

105. ARTHUR A. THOMPSON, *ECONOMICS OF THE FIRM: THEORY AND PRACTICE* 126 (5th ed. 1989).

106. *F.T.C. v. Whole Foods Mkt., Inc.*, 548 F.3d 1028, 1037–39 (D.C. Cir. 2008).

107. U.S. DEP'T OF JUST. & F.T.C., *HORIZONTAL MERGER GUIDELINES* § 4.1.4 (2010), <http://www.justice.gov/atr/public/guidelines/hmg-2010.html> [<https://perma.cc/7DRK-P2HB>].

108. *Whole Foods Mkt.*, 548 F.3d at 1038–39.

109. *Id.*

the inframarginal ones during the recoupment period. Below-cost price cuts would only be offered to the marginal customers, and the supra-competitive pricing in pursuit of recoupment only to the inframarginal ones.

One obvious problem with such an approach, however, is that it is highly unlikely that the same group of customers will be subject to both the price cut and the post-predation price increase. Even in the absence of algorithmic targeting, the customers are not necessarily the same, as the composition of customers can change over time. There is no reason to assume that the exact same customers populate the market during the predation and the recoupment periods. In the presence of algorithmic targeting, the beneficiaries of the price cut and the victims of the price increase would be even less likely to coincide. It is the marginal customers who are most likely to be lured by competing products and thus offered price cuts.¹¹⁰ Meanwhile, it is the inframarginal customers who are most susceptible to price increases during the recoupment period, as they have lower price elasticity of demand.¹¹¹ If the relevant market is defined as the marginal customers, recoupment is likely to fail, as the dominant firm will not recoup its predation loss from this group of customers. If the relevant market is defined as the inframarginal customers, there is no predation loss in the first place, and hence nothing to recoup. This selective market definition approach will not suffice.

Another possible adjustment to the actual profit standards that may render them more practical is perhaps to limit the calculation to those customers/or transactions that have been affected by the predation scheme. In other words, when ascertaining the predation loss, profits from the inframarginal customers who have not been offered the price cut are excluded. Likewise, only profits from those inframarginal customers who have been subject to post-predation monopolistic price increases should count toward the post-predation gain. To determine whether successful recoupment is probable, the comparison will be between the predation loss and post-predation gains thus calculated. This would allow the analysis to capture both the predation loss and the recoupment gain while avoiding the dilution of the effects of predation.

Although this would solve the problem created by selective market definition, it faces another difficulty. It is highly unlikely that a significant portion of the post-predation inframarginal customers benefited from the initial price cut. This result is the very problem identified by Christopher

110. *Id.*

111. William S. Comanor, *Vertical Price-Fixing, Vertical Market Restrictions, and the New Antitrust Policy*, 98 HARV. L. REV. 983, 991 (1985).

Leslie about the recoupment requirement: the fact that the dominant firm fails to recoup its loss from the market overall does not mean that there is no consumer harm.¹¹² The group of customers who benefit from the price cut need not be the same group of customers who suffer from the monopolistic price increase.¹¹³ Even if recoupment fails and the overall consumer gain outweighs its loss, some customers may still be harmed. In Leslie's case, he argues that the composition of customers may change over time.¹¹⁴ The same customer may not buy during both the predation period and the recoupment period. In our case, the mismatch between those benefited and harmed will persist even if the composition of customers remains constant over time. A significant post-predation shift of customers from marginal to inframarginal is unlikely.

iii. Abolishing the recoupment requirement

One further option would be to abolish the recoupment requirement altogether. Before one can decide whether to pursue this option, a closer look at the justifications for the requirement is warranted. Three justifications have been offered for requiring a proof of recoupment under a predatory pricing claim. The first justification is that customers are only harmed if the predator successfully recoups its losses.¹¹⁵ Otherwise, predatory pricing is actually a boon to customers. The second one is that predatory pricing is only rational behavior on the part of the predator if it is profitable overall, and profitability requires successful recoupment.¹¹⁶ While we usually do not require a proof of the economic rationality of monopolistic or abusive conduct,¹¹⁷ mandating such a proof in the case of predatory pricing is defensible because the line between permissible price cutting and predatory pricing is a very fine one. Moreover, price cutting is the very conduct that antitrust law welcomes, if not encourages.¹¹⁸ The third justification is based on the grounds of administrability. The idea is that probability of recoupment acts as a screen for predatory pricing cases.¹¹⁹ Such a screen would only make sense, however, if probability of recoupment is somehow easier to prove than other elements of a predatory pricing claim, and there is a high

112. Leslie, *supra* note 49, at 1742.

113. *Id.*

114. *Id.*

115. *Brooke Grp. Ltd.*, 509 U.S. at 224.

116. *Id.*

117. See Gregory J. Werden, *Identifying Exclusionary Conduct Under Section 2: The "No Economic Sense" Test*, 73 ANTITRUST L.J. 413 (2006).

118. *Barry Wright Corp. v. ITT Grinnell Corp.*, 724 F.2d 227, 234 (1st Cir. 1983).

119. Leslie, *supra* note 49, at 1710.

degree of correspondence between successful recoupment and exclusionary predatory pricing.¹²⁰

First justification

The first justification has already been addressed. The aggregation of predation loss and gain would only be a valid determination of consumer harm if the victims of the loss were also recipients of the gain. Where such an identity between the victims and the beneficiaries does not exist, there are bound to be victims of post-predation monopolistic pricing who are not compensated by the below-cost price cutting. Where algorithmic targeting is effective, there is a very high likelihood that the victims and the beneficiaries will be different and that the number of victims is not small. In fact, there is likely to be an almost complete mismatch between the victims and the beneficiaries. Therefore, the probability of recoupment would be a very poor indicator of consumer harm.

There are two possible ways to understand the kind of consumer harm that successful recoupment is meant to indicate. First, that there is unrecompensed harm suffered by some consumers, and, second, that consumers overall suffer net harm.¹²¹ In other words, there is either gross or net consumer harm. If successful recoupment is understood in the gross sense to signify some unrecompensed harm, the proof of failed recoupment would be very straightforward. All that is required is a showing that some victims of post-predation monopolistic pricing did not enjoy below-cost price cutting during the predation period. There is no need to prove that the gain is larger than the predation loss overall. The mismatch between the victims and the beneficiaries exacerbated by algorithmic targeting means that recoupment would always be successful in this sense.

If successful recoupment is understood in the second sense, that consumers suffer overall net harm, two things need to be borne in mind. As our practical example above shows, algorithmic targeting renders recoupment more likely. Moreover, a showing of failed recoupment is cold comfort to victims of predation unless there is evidence of transfer from the beneficiaries to the victims. Such transfers are highly implausible in real life.¹²² There seems to be no good reason to require such an elaborate proof of recoupment just to show there is no net consumer harm overall, when such

120. Kaplow, *supra* note 49, at 9–15.

121. This would be based on a Kaldor-Hicks notion of efficiency. See RICHARD O. ZERBE, *ECONOMIC EFFICIENCY IN LAW AND ECONOMICS* 4–5 (2001).

122. Pol Antràs, Alonso de Gortari & Oleg Itskhoki, *Globalization, Inequality and Welfare*, 108 J. INT'L ECON. 387, 388 (2017).

a showing would be largely meaningless. Therefore, the first justification for the recoupment requirement can be readily dismissed.

Second justification

Regarding the second justification focusing on the rationality of the predatory conduct, one must ask: what does a proof of economic rationality add to the analysis? Steven Salop argues that:

[T]he profit-sacrifice standard is a test of anticompetitive purpose and intent. That is, if a profit-maximizing firm engages in conduct that would not be economically rational (i.e., maximally profitable) absent a reduction in competition, then it can be inferred that the firm must have intended to cause the anticompetitive effect.¹²³

In other words, given that it is hard to distinguish benign from anticompetitive below-cost price cutting based on effects, we need to resort to intent evidence.¹²⁴ However, documentary intent evidence can be unreliable for a variety of reasons. It can be so because corporate documents can be full of aggressive statements that could be interpreted as evidence of predatory intent when they are nothing more than puffery or corporate bravado.¹²⁵ It can also be unreliable because potential offenders may be tempted to fabricate exculpatory evidence once they know that such evidence will be taken into account by the courts.¹²⁶ Therefore, we must further resort to evidence of objective intent, which hinges on the profitability of the conduct.¹²⁷ The argument is that a profit-maximizing firm would not undertake unprofitable conduct. If the predatory scheme turns out to be unprofitable, the dominant firm must not have intended predation.

Before proceeding further, a more precise definition of predatory intent is called for. Obviously when a firm cuts prices, it wants to take business from its rivals. That is normal business conduct and does not evince a predatory intent.¹²⁸ The lynchpin for predation is the elimination of rivals in

123. Salop, *supra* note 57, at 320.

124. Steven R. Beck, *Intent as an Element of Predatory Pricing Under Section 2 of the Sherman Act*, 76 CORNELL L. REV. 1242 (1991).

125. Ronald A. Cass & Keith N. Hylton, *Antitrust Intent*, 74 S. CAL. L. REV. 657, 675–76, 676 n.66 (2001).

126. Christopher R. Leslie, *How to Hide a Price-Fixing Conspiracy*, 2021 U. ILL. L. REV. 1199, 1225–28 (2021) (noting how price-fixing conspirators falsifying documents to conceal their illegal collusion).

127. Leslie, *supra* note 49, at 1754–56.

128. Easterbrook, *supra* note 85, at 280–81.

order to take over the market.¹²⁹ Therefore, a predatory intent must entail a desire to take sufficient business from rivals such that they are eliminated from the market or cease to exert effective competitive constraint on the predator.

The possibility of algorithmic targeting requires some reassessment of the link between success of recoupment and economic rationality. First and foremost, the foregoing discussion makes clear that the possibility of algorithmic targeting would significantly minimize the predation loss. When predation loss is expected to be substantial, it is fair to surmise that firms will not embark on predation lightly. Given the size of the “investment,” one can expect the predating firm to be fairly certain of success before embarking on it. In this case, requiring a proof of successful recoupment is more persuasive. But when the predation loss is much smaller and predation much more easily reversible (individualized discounts probably can be withdrawn without many customers noticing), firms may be more tempted to give it a try, even though they are less confident of successful recoupment. The perception of the probability of recoupment plays a critical role in linking the prospect of recoupment with predatory intent. This link is much more tenuous in the presence of algorithmic targeting.

Furthermore, it is worth pondering the meaning of intent in the age of algorithmic targeting. There are two ways in which algorithms can be deployed to aid in algorithmic targeting. One type of algorithm, called monitoring algorithms, “can help businesses to collect data related to buyer preferences or to competitors through the use of scraping.”¹³⁰ The second type of algorithm makes pricing decisions.¹³¹ If only the former type of algorithm is deployed, “the actual execution of pricing is entirely done by human judgment.”¹³² When pricing algorithms are used, the pricing process can be understood as “embedded optimization where real-time pricing decisions are automated.”¹³³ When the pricing decisions are ultimately made by humans, the analysis of intent is no different from where algorithms are

129. Paul L. Joskow & Alvin K. Klevorick, *A Framework for Analyzing Predatory Pricing Policy*, 89 *YALE L.J.* 213, 259 (1979).

130. Christophe Samuel Hutchinson, Gulnara Fliurovna Ruchkina & Sergei Guerasimovich Pavlikov, *Tacit Collusion on Steroids: The Potential Risks for Competition Resulting from the Use of Algorithm Technology by Companies*, 13 *SUSTAINABILITY* 951, 953 (2021).

131. Cassey Lee, *The Landscape of Pricing and Algorithmic Pricing* 21 (ISEAS-Yusof Ishak Inst., Working Paper No. 2020-06, 2020), <https://www.iseas.edu.sg/articles-commentaries/iseas-economics-working-papers/the-landscape-of-pricing-and-algorithmic-pricing/> [https://perma.cc/H9NF-ZT32].

132. *Id.*

133. *Id.*

not involved. Yet, when pricing decisions are made by a pricing algorithm, the question of intent depends on the type of algorithm at issue.

There are two main types of pricing algorithms, adaptive algorithms and learning algorithms. The former “are, essentially, sets of rules that dictate optimal responses to specific contingencies.”¹³⁴ The latter goes beyond adaptive algorithms where, with the assistance of machine learning, “the software learns how to solve the task from experience.”¹³⁵ Adaptive algorithms perform two functions: estimation and optimization. The algorithm “estimates market demand using past volumes and prices, and possibly other control variables,”¹³⁶ and then “chooses the optimal price given the demand estimate and observed past behavior of rivals.”¹³⁷ In contrast, 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.”¹³⁸

What an adaptive algorithm does depends on what it is programmed to do. The set of rules given to it essentially dictates its operation.¹³⁹ If an adaptive algorithm is programmed to predate, the predatory intent is self-evident and there is no need to resort to likelihood of recoupment to demonstrate intent. The question becomes more complicated when a learning algorithm is merely programmed to maximize profits but nonetheless resorts to below-cost price cutting through machine learning. When a profit-maximizing pricing algorithm offers targeted prices to certain groups of customers, it does so because it maximizes short-term profit.¹⁴⁰ If a learning algorithm that is programmed to be profit-maximizing nonetheless engages in below-cost price cutting, it must be because it believes that predatory pricing maximizes profit.¹⁴¹ It may be difficult for the firm deploying the algorithm to know “which variables it [the algorithm] was using to set a particular price, and may not be aware of whether any increase in profit was

134. Emilio Calvano et al., *Algorithmic Pricing What Implications for Competition Policy?*, 55 REV. INDUS. ORG. 155, 158 (2019).

135. *Id.* at 160.

136. *Id.* at 158.

137. *Id.*

138. *Id.* at 160.

139. *Id.* at 158–61.

140. 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/QHK8-VD7G>] [hereinafter PRICING ALGORITHMS].

141. Calvano et al., *supra* note 134, at 161–65.

due to attracting additional customers, charging higher prices to loyal customers, or tacit coordination.”¹⁴² What it does know is that a profit-maximizing learning algorithm would only offer below-cost prices if it anticipates successful recoupment and hence “intends” to pursue predation.

If a learning algorithm that is programmed to be economically rational pursues predation, an inquiry about the likelihood of recoupment would only tell us whether the algorithm miscalculates or otherwise fails to assess market conditions accurately. There are two theoretical scenarios in which recoupment may fail. First, the predator knows all along that recoupment is unlikely but nonetheless persists with below-cost price cutting, with or without a predatory intent. One instance of below-cost pricing without expectation of ultimate profit would be if the predator is trying to establish a reputation of general toughness across multiple markets.¹⁴³ There may be no rational expectation of profit in the market in which predation takes place, but profitability is expected firmwide. Second, the predator expects successful recoupment, but its expectation is frustrated by subsequent events.¹⁴⁴ Actual recoupment fails despite original expectations to the contrary.

A profit-maximizing learning algorithm would never launch a predation scheme without rational expectations of recoupment. The first scenario can be ruled out except for scenarios where profitability is measured across markets. This means that the only circumstance under which we will observe below-cost price cutting without eventual successful recoupment is when the algorithm’s calculations have not been borne out by reality. This could be due to miscalculation or unforeseen circumstances. In either case, successful recoupment was expected, which means the algorithm expected the predation scheme to be profitable, which in turn indicates a predatory intent. This is not the inference that is supposed to be drawn from failed recoupment.¹⁴⁵

If a learning algorithm is programmed to be always economically rational and profit-maximizing, it becomes superfluous to expend so much time and energy to establish likelihood of recoupment to demonstrate a predatory intent. If recoupment succeeds, the algorithm’s calculations are vindicated. If recoupment fails, the algorithm miscalculated, which bears no relevance to the legality of the below-cost price cutting scheme. Success of recoupment is thus a meaningless factor in the world of algorithmic targeting and pricing.

142. PRICING ALGORITHMS, *supra* note 140, at ¶ 2.10.

143. Kaplow, *supra* note 49, at 56.

144. *Id.* at 57.

145. *Id.* at 4, 60.

With algorithmic pricing, intent can be tackled both at the level of the algorithm and the level of the decision to adopt the algorithm. As mentioned earlier, if a firm adopts an algorithm that is programmed to be predatory, the predatory intent is obvious and should not require elaborate proof by way of likelihood of recoupment. The analysis of intent becomes more complicated if a firm adopts a learning algorithm that turns out to be predatory. The issue is not confined to predatory intent. It also arises in situations of algorithmic collusion.¹⁴⁶ One may argue that the end result achieved by the algorithm should not be imputed to the firm adopting it unless the result is reasonably foreseeable.

The imputation of algorithmic intent is beyond the scope of this article. It has been suggested that even for deep learning algorithms that are often analogized as “black boxes,” it is possible to audit their inner workings, for example, to detect implicit racial bias.¹⁴⁷ Therefore, it may be possible to audit learning algorithms for predatory intent. Suffice it to note that whatever the final legal test is, the likelihood of recoupment as estimated by the algorithm has no relevance to its predatory intent.

Taking a step back, it is worth pondering whether it is necessary to rely on likelihood of recoupment as a manifestation of economic rationality. It is important to recall the other element of a predatory pricing claim: below-cost price cutting. Regardless of whether recoupment is a threshold element,¹⁴⁸ eventually a plaintiff must show that the dominant firm charged a price below some appropriate measure of costs.¹⁴⁹ The entire rationale of the cost measure is to show that the dominant firm is charging a price so low that it is no longer economically rational for it to continue to supply the market. Therefore, if it is decided that economic irrationality must be shown in a predatory pricing claim, the element of below-cost pricing already serves that purpose. In any case, the assumption that predatory pricing is economically irrational is highly questionable and has been subject to challenge.¹⁵⁰

146. Timo Klein, *Autonomous Algorithmic Collusion: Q-Learning Under Sequential Pricing* 30–31 (Tinbergen Inst., Discussion Paper TI 2018-056/VII, Nov. 2020), <https://papers.tinbergen.nl/18056.pdf> [<https://perma.cc/55A7-HWUR>].

147. PRICING ALGORITHMS, *supra* note 140, at ¶ 9.1.

148. Kaplow, *supra* note 49, at 19.

149. Philip Areeda & Donald F. Turner, *Predatory Pricing and Related Practices under Section 2 of the Sherman Act*, 88 HARV. L. REV. 697, 712 (1975). We explore cost measurements further down, in Section III.C.

150. Sandeep Vaheesan, *Reconsidering Brooke Group: Predatory Pricing in Light of the Empirical Learning*, 12 BERKELEY BUS. L.J. 81 (2015) (identifying examples of predatory pricing); Christopher R. Leslie, *Rationality Analysis in Antitrust*, 158 U. PA. L. REV. 261, 319–24 (2010) (explaining the rationality of predatory pricing).

Critics may argue that below-cost pricing only shows irrationality of the conduct at one moment in time, while successful recoupment demonstrates the profitability and hence rationality of the predation scheme overall.¹⁵¹ It is unclear, however, why irrationality of price cutting at one moment in time should not suffice to demonstrate predatory intent. Apart from some justifications for short-term below-cost price cutting, such as promotion of a new product and clearance of seasonal or soon-to-expire stock,¹⁵² there seems to be no good reason why a profit-maximizing firm would want to offer below-cost prices at all, no matter how brief the offer is. It is irrational for a dominant firm to charge below-cost prices even for a short time. There is no need to evaluate the rationality of the predation scheme over its entire duration. And if below-cost pricing at one moment in time suffices to demonstrate economic irrationality, likelihood of recoupment becomes superfluous.

Third justification

The final justification for the recoupment requirement is administrability. The argument is that recoupment is easier to prove than below-cost pricing.¹⁵³ Therefore, recoupment should be used to screen out meritless cases. Yet it is not clear that recoupment is necessarily easier to prove and therefore provides a good screen.¹⁵⁴ Recall that it was argued earlier that the actual profit standards are no longer a useful benchmark should algorithmic targeting become feasible. Various possible adjustments either do not work or contradict the very rationale for using recoupment as an indication of consumer harm. And the hypothetical profit standards have already been dismissed as impractical. The only feasible approach to proving recoupment would be the indirect approach, which itself only provides a rough approximation of recoupment. Moreover, as discussed above, traditional structural elements seem to have less relevance in a world of algorithmic targeting where they provide limited information about the ability to recoup and where recoupment might be possible even in the absence of such structural elements.

More importantly, the recoupment requirement would only serve as a useful screening device if it independently sheds light on the merit of a predatory pricing claim. Kaplow has convincingly argued that the various elements of a predatory pricing claim form an integrated inquiry and cannot

151. Kaplow, *supra* note 49, at 2.

152. Areeda & Turner, *supra* note 149, at 722–24.

153. Leslie, *supra* note 49, at 1710–12.

154. Kaplow, *supra* note 49, at 15.

be segregated as distinct components or designated as a threshold inquiry.¹⁵⁵ The probability of recoupment on its own does not tell us whether a price cutting scheme is exclusionary or predatory.¹⁵⁶ As argued previously, successful recoupment does not indicate greater consumer harm or the presence of a predatory intent.

Administrability on its own cannot justify maintaining the recoupment requirement. Given that algorithmic targeting would render recoupment more likely, the requirement would lose much of its informational value. There are scant reasons for maintaining a requirement that gives us little useful information but is difficult to establish. Leslie's call for the abolition of the requirement would be more powerful in a world of algorithmic targeting.¹⁵⁷

The recoupment requirement has been used as a filter in predatory pricing cases in the United States.¹⁵⁸ The foregoing discussion casts further doubt on whether the criterion can sensibly be applied should algorithmic targeting become prevalent in the future. Abolishing the requirement would shift the focus to price-cost comparison. This would bring U.S. law in line with EU competition law, under which proof of recoupment is not needed.¹⁵⁹ Yet a price-cost comparison in the world of algorithmic targeting is not without its own problems. This will be explored in the next sections.

C. Algorithmic Targeting and the Appropriate Price for Price-Cost Comparison

The possibility of algorithmic targeting would also have implications for the price-cost comparison in a predatory pricing claim. In a standard predatory pricing claim, there is a comparison between the defendant's price and some measure of the defendant's cost. The controversy is usually centered on the appropriate cost measure. Since Areeda and Turner's seminal article, commentators have been engaged in a long-running debate about the appropriate cost measure. Marginal cost,¹⁶⁰ average variable cost,¹⁶¹ average

155. Louis Kaplow, *Recoupment, Market Power, and Predatory Pricing*, 82 ANTITRUST L. J. 167 (2018).

156. Leslie, *supra* note 49, at 1741–44.

157. *Id.* at 1765.

158. *Id.* at 1710.

159. Case C-202/07 P, *France Telecom v. Comm'n*, 2009 E.C.R. I-2369, ¶¶ 110–13.

160. Areeda & Turner, *supra* note 149, at 709–13.

161. *Id.* at 716–18.

avoidable cost,¹⁶² and average incremental cost¹⁶³ have all been proposed at one point or another as the appropriate cost measure. The possibility of algorithmic targeting has relevance to this debate, which will be explored below. The impact of algorithmic targeting is not limited, however, to the cost side of the comparison. It creates complications for the ascertainment of price for the simple reason that there is no longer one price prevailing in the market that can be used for the comparison.

In the usual predatory pricing case, the defendant's price will be compared with some measure of its cost to determine whether the dominant firm is charging a below-cost price.¹⁶⁴ Under the prevailing case law, there can be no viable predatory pricing claim without a below-cost price.¹⁶⁵ With one uniform market price, it is relatively straightforward to identify the appropriate price for the purpose of the price-cost comparison. Yet, identifying a prevailing price would no longer be a straightforward endeavor once algorithmic targeting is possible. Multiple prices would prevail in the market as customers are offered different prices.

The question arises as to which price should be used for the comparison—whether it should be one price offered to a particular customer at a particular point in time, or some composite price. The obvious answer would be the average price offered to all customers, calculated the same way as the average variable cost is calculated. Total revenue can be divided by the total number of units sold to obtain an average price.¹⁶⁶ This, however, would run into the same problem that arose in the context of recoupment, that of understating the loss. Total revenue necessarily would include revenue derived from sales to inframarginal customers where no price cutting was undertaken. Including the revenue from sales to these customers would inflate the price used for the price-cost comparison, thereby artificially reducing the incidence of a finding of below-cost price. The correct approach would require that sales to the inframarginal customers be excluded in the calculation. Thus, the EU Commission in its discussion of predatory rebates in the Guidance Paper on the enforcement of the then-Article 82 (hereinafter the “Guidance Paper”) suggests focusing on the price

162. William J. Baumol, *Predation and the Logic of the Average Variable Cost Test*, 39 J.L. & ECON. 49, 60–62 (1996).

163. Aaron S. Edlin, *Predatory Pricing: Limiting Brooke Group to Monopolies and Sound Implementation of Price-Cost Comparisons*, YALE L.J.F. 996, 1008–11 (2018).

164. Areeda & Turner, *supra* note 149.

165. At least that is so under current law. Some scholars have disputed that only below-cost price cutting is exclusionary. *See, e.g.*, Aaron S. Edlin, *Stopping Above-Cost Predatory Pricing*, 111 YALE L.J. 941 (2002).

166. RICHARD G. LIPSEY & CHRISTOPHER RAGAN, *ECONOMICS* 210 (10th ed. 2003).

paid for the “‘contestable’ portion of demand.”¹⁶⁷

The exclusion of the inframarginal customers would require identification of marginal and inframarginal customers. If the new entrant itself is not able to practice algorithmic targeting and can only offer one price to all the dominant firm’s existing customers, the dominant firm would only need to undercut the entrant’s price slightly to forestall the exodus of the marginal customers. There is no overriding reason for the dominant firm to offer highly varied prices to these susceptible customers to hold on to them. In that case, one price would apply to all the customers who enjoy a price cut. That price can be used in the price-cost comparison.

To the extent that it is possible to discern the classification of customers from the dominant firm’s internal system or algorithm,¹⁶⁸ the task of calculating an average price would be relatively straightforward.¹⁶⁹ Otherwise it would only be possible to identify the marginal customers through the price cuts offered by the firm in response to a competitive threat. When a new firm enters the market, a dominant firm that is capable of implementing algorithmic targeting would lower prices for customers who may be lured by the new offering but would not lower prices for the loyal customers. The former would be the marginal customers whose prices should be used for calculating the appropriate price for price-cost comparison. A more detailed discussion of the identification of the marginal customer will be provided subsequently. The total revenue derived from sales to these marginal customers would be divided by the total units sold to these customers to obtain an average price.

D. Algorithmic Targeting and the Appropriate Cost Measure

1. The Appropriate Cost Measure: The Existing Debate

Much more scholarly attention has been paid to the issue of cost in the price-cost comparison.¹⁷⁰ A variety of cost measures have been offered for the price-cost comparison, including “(1) average variable cost; (2) marginal cost; (3) an exclusive measure of average incremental cost from some well-identified incremental increase in output during the predatory period; or (4)

167. Guidance on the Commission’s Enforcement Priorities in Applying Article 82 of the EC Treaty to Abusive Exclusionary Conduct by Dominant Undertakings, 2009 O.J. (C 45) ¶ 39 [hereinafter Article 82 Guidance]. See in particular *id.* at ¶ 41.

168. PRICING ALGORITHMS, *supra* note 140, at ¶ 9.1.

169. Klein, *supra* note 146, at 31.

170. See, e.g., Areeda & Turner, *supra* note 149; Baumol, *supra* note 162; Edlin, *supra* note 163.

an inclusive measure of average incremental cost that includes revenue reductions on pre-existing (inframarginal) units of output.”¹⁷¹ Each of these cost measures has been criticized and defended by different commentators. The purpose of our inquiry is to figure out which of these cost measures would be appropriate in a world of algorithmic targeting, and whether any of these cost measures would need adjustments to be fit for purpose.

a. Marginal cost

Philip Areeda and Donald Turner originally propose marginal cost¹⁷² (MC) as the relevant cost measure in their seminal article on predatory pricing.¹⁷³ They note that MC is the relevant cost measure because, “in deciding whether it would increase or decrease output, the firm looks to the *incremental* effects on revenue and costs.”¹⁷⁴ They add that there are no rational justifications for a dominant firm to price below MC because when price is below MC, the firm will be both incurring a loss and wasting society’s resources by continuing its production.¹⁷⁵

A number of commentators have criticized MC as a cost measure. Aaron Edlin criticizes the marginal cost test as one-sided because while below-MC pricing clearly entails profit sacrifice, “[n]othing is proven if price exceeds marginal cost.”¹⁷⁶ The essence of his argument is that pricing above MC does not rule out the possibility of profit sacrifice.¹⁷⁷ A price above MC may nonetheless fail to increase profit. If a firm offers uniform prices to all customers, a price above MC could still require the dominant firm to reduce prices offered to the inframarginal customers such that overall profitability is reduced.¹⁷⁸ The firm may still sacrifice profits even though the price is above MC.¹⁷⁹ For example, a firm may be offering each unit of widget to ten customers at the uniform price of \$5. To entice the marginal customer, the firm has to lower the price to \$4 to all customers when the MC for the marginal unit is \$3. Price is clearly above MC, but selling this marginal unit lowers the firm’s overall profit. The marginal sale would be a profit-sacrificing one for the firm. William Baumol similarly

171. Edlin, *supra* note 163, at 1012.

172. Marginal cost is the cost associated with the production of one additional unit.

173. Areeda & Turner, *supra* note 149, at 701–02.

174. *Id.* (italics in original).

175. *Id.* at 712.

176. Edlin, *supra* note 163, at 1006.

177. *Id.* at 1006–07.

178. *Id.* at 1007.

179. *Id.*

characterizes the marginal cost test as “not altogether convincing,”¹⁸⁰ and “not get[ting] at the issue.”¹⁸¹ Echoing Edlin’s view, Baumol asserts that:

[T]here is simply no way in which one can infer from the fact that the firm adopts a price that exceeds MC that this will constitute a net addition to long-run profits relative to what the firm might otherwise have earned, nor can one legitimately conclude that a price that falls short of MC must reduce those profits in the absence of destruction of competitors.¹⁸²

b. Average variable cost

Having argued for a marginal cost test, Areeda and Turner concede that MC is very difficult to ascertain in practice, as it is not a cost measure that accountants are familiar with and that accountants calculate.¹⁸³ They proceed to propose average variable cost¹⁸⁴ (AVC) as a proxy for MC, and various modifications to a dual-cost rule involving both marginal cost and average variable cost.¹⁸⁵ Einer Elhauge summarizes the convoluted rule ultimately proposed by Areeda and Turner as follows:

[I]n the end Areeda, Turner, and Hovenkamp really embrace a three-staged cost test: (1) when below the output that minimizes average variable costs, use average variable costs; (2) when between the outputs that minimize average variable and total costs, use average variable costs unless marginal costs are significantly higher; and (3) when above the output that minimizes average total costs, use average total costs.¹⁸⁶

A number of commentators have defended the use of AVC as the appropriate cost measure on a number of grounds. Some have argued that AVC is an appropriate test because a rational profit-maximizing firm has no reason to charge a price below AVC. Paul Joskow and Alvin Klevorick sum up this view best when they assert that “a price cut to a point below average variable cost can have no purpose other than the sacrifice of short-run profits for long-run monopoly gain.”¹⁸⁷ Such a price is never profit-maximizing in the short run and is likely to be below the long run costs of an as-efficient

180. Baumol, *supra* note 162, at 54.

181. *Id.* at 55.

182. *Id.*

183. Areeda & Turner, *supra* note 149, at 716.

184. Average variable cost equals the total variable costs divided by the number of units sold.

185. Areeda & Turner, *supra* note 149, at 717–18.

186. Elhauge, *supra* note 88, at 705.

187. Joskow & Klevorick, *supra* note 129, at 251.

competitor. William Baumol and Herbert Hovenkamp have expressed similar views.¹⁸⁸ The AVC test has also been defended on the grounds of administrability, as AVC is much easier to calculate than MC.¹⁸⁹ The test is used by the European Court of Justice to establish a presumption of predation.¹⁹⁰

The AVC has not been immune from criticism, however. Similar to the MC test, Edlin condemns the one-sided nature of the AVC test.¹⁹¹ Hovenkamp notes that AVC is not without its own difficulties in calculation. The line between fixed and variable costs is not always clear, and joint costs in a multi-product firm can be very tricky to allocate across the various product lines.¹⁹² In fact, Elhauge argues that fixed and variable costs cannot be defined in a general manner and instead depends “solely on whether they could be varied during the time period of the alleged predation.”¹⁹³ Hovenkamp further remarks that AVC has a tendency to be overly lenient to defendants at high levels of output where MC and AVC diverge significantly, which renders AVC a poor proxy for the MC test.¹⁹⁴

There are two additional conceptual difficulties with the AVC test. The first one is that inferring the efficiency of production of a firm from its AVC can be problematic because the level of a firm’s AVC can be affected by its choice of technology.¹⁹⁵ A capital intensive firm can have lower AVC even though it may in fact be less efficient than a labor-intensive firm, which by nature incurs higher variable costs.¹⁹⁶ Therefore, using the dominant firm’s AVC as the benchmark for the price-cost comparison may inadvertently fail to offer protection to an equally efficient if not more efficient competitor. The second one is that using AVC as a proxy for MC could give the dominant firm the incentive to maintain inefficient excess capacity so that it will enjoy the benefit of the AVC being lower than the MC.¹⁹⁷ When a firm operates with excess capacity, and thus to the right of the minimum of AVC where AVC coincides with MC, AVC falls below MC and thus provides the

188. Baumol, *supra* note 162, at 56; Herbert Hovenkamp, *The Law of Exclusionary Pricing* 4 (U. Iowa Legal Stud. Rsch. Paper, No. 05-34, 2006), <https://dx.doi.org/10.2139/ssrn.876968>.

189. Hovenkamp, *supra* note 188, at 4.

190. Case 62/86, *AKZO Chemie BV v. Comm’n of the Eur. Cmty.*, 1991 E.C.R. I-3359, ¶ 71.

191. Edlin, *supra* note 163, at 1007.

192. Hovenkamp, *supra* note 188, at 4.

193. Elhauge, *supra* note 88, at 708.

194. Hovenkamp, *supra* note 188, at 5–6.

195. Joseph F. Brodley & George A. Hay, *Predatory Pricing: Competing Economic Theories and the Evolution of Legal Standards*, 66 *CORNELL L. REV.* 738, 754 (1981).

196. Elhauge, *supra* note 88, at 711.

197. *Id.* at 716–17.

dominant firm a more lenient standard by which its pricing is judged.

c. Average incremental cost and average avoidable cost

The final set of tests to be discussed are based on average incremental cost (AIC) and average avoidable costs (AAC). According to Edlin, the AIC test is “another useful one-sided test [that] compares price with average incremental cost, a cost measure found by dividing the cost of producing the identified output increase by the number of units of increased production.”¹⁹⁸ The AIC can be measured in the short run and the long run. Over the long run, AIC “is the per unit cost of producing the predatory increment of output whenever such costs were incurred.”¹⁹⁹ In particular, long run AIC includes all product research, development, and marketing costs incurred for the production of a predatory new product or a predatory increase in production of an existing product, including all the sunk costs incurred.²⁰⁰ Long run AIC, or LRAIC, is used by the European Commission to establish a kind of safe harbor. Where the effective price is above the LRAIC, the Commission does not see much room for predation.²⁰¹

A related and very similar concept is the average avoidable costs (AAC), which was proposed by William Baumol²⁰² and features also in the European Commission’s Guidance Paper as “the appropriate starting point.”²⁰³ AAC “is the average per unit cost that predator would have avoided during the period of below cost pricing had it not produced the predatory increment of sales.”²⁰⁴ Thus, if the period of alleged predation is ten months, AAC is the sum of the costs incurred in producing the predatory increment over the ten month period divided by the quantity produced. In particular, AAC “exclude inescapable sunk costs ‘that cannot be avoided for some limited period of time’ but include any unsunk fixed costs that ‘must be incurred in a lump in order for any output at all to be provided.’”²⁰⁵

Baumol clarifies that AIC is usually greater than AAC because AIC includes inescapable sunk costs that must be incurred when increasing production that can only be avoided in very long run.²⁰⁶ AAC is a short-run concept because over the long run, all costs, including previously

198. Edlin, *supra* note 163, at 1008.

199. Bolton et al., *supra* note 95, at 2272.

200. *Id.*

201. Article 82 Guidance, *supra* note 167, at ¶¶ 43–44, 60, 80.

202. Baumol, *supra* note 162.

203. Article 82 Guidance, *supra* note 167, at ¶ 64.

204. Bolton et al., *supra* note 95, at 2271.

205. Elhauge, *supra* note 88, at 706 (quoting Baumol, *supra* note 162, at 57 n.13, 58–59).

206. Baumol, *supra* note 162, at 58; Article 82 Guidance, *supra* note 167, at ¶ 26.

inescapable sunk costs, should be avoidable.²⁰⁷ Over the long run, avoidable costs should be the same as incremental costs, as all the costs that are incurred as a result of the increased production of a product should be avoidable.

One of the controversies regarding the price-cost comparison is whether foregone profits as a result of the price reduction on the inframarginal units should count toward the cost of predation. In order to incorporate foregone profits, Edlin proposes a comparison between the incremental revenue and the incremental costs of the output expansion that helps to bring prices down to the allegedly predatory level. In this incremental revenue-cost comparison, the foregone profits are either subtracted from the revenue or added to the cost.²⁰⁸

According to Elhauge, this effectively turns the predatory pricing claim into a profit maximization obligation, which he rejects.²⁰⁹ He argues that “it is vital for analytical clarity to avoid using cost measures that effectively include forgone profits. Otherwise, one cannot keep predatory theories based on a failure to maximize short-term profits analytically distinct from theories based on pricing below costs.”²¹⁰ In contrast, Edlin insists that the incremental revenue-cost comparison is in fact the “ideal” test because it directly measures sacrifice.²¹¹ Edlin therefore advocates an inclusive measure of costs that includes foregone profits, whereas Elhauge supports an exclusive measure of costs that does not include such profits. This harkens back to the debate between the hypothetical profit standards and the actual profit standards.

2. The Appropriate Cost Measure in the World of Algorithmic Targeting

One of the fundamental ways in which algorithmic targeting changes the debate about predation and cost measurements relates to the inclusion of foregone profits. Although this question may have salience in the pre-digital age, it has little relevance once algorithmic targeting is possible. The dominant firm would no longer be required to lower prices on the inframarginal units of output, which would entail profit sacrifice on the inframarginal units. Forgone profits would be kept to a minimum even when predatory pricing is being pursued.

207. Bolton et al., *supra* note 95, at 2271–72.

208. Elhauge, *supra* note 88, at 694.

209. *Id.*

210. *Id.* at 694.

211. Edlin, *supra* note 163, at 1010–11.

This change exemplifies the need for a more fundamental rethink of the various cost measures for predatory pricing. It is clear that concepts such as marginal cost and average variable cost only makes sense if output is measured on a firmwide basis. Marginal cost changes are measured at the overall output level, and MC does not make sense as a concept when output is measured in smaller increments.²¹² Average variable cost need not be measured across the entire output. In fact, Elhauge argues that measuring AVC across the entire output would deprive an equally efficient rival of adequate protection of predatory pricing.²¹³ To remedy this shortcoming of the AVC test, he asserts that the relevant increment over which the AVC should be measured is not the dominant firm's entire output, but its incremental output that displaces the output of an entering competitor.²¹⁴ This is due to the fact that what matters is rival exit (or nonentry), and thus it needs to be examined who is more efficient at producing "the rival's output."²¹⁵ To Elhauge, the appropriate cost measure should encapsulate "all costs of the allegedly predatory increase in output that replaces the rival's output that are variable to the predator during the period of alleged predation."²¹⁶ In other words, Elhauge seems to embrace the AIC test with the caveat of the exclusion of foregone profits.

Although there are minor disagreements as to whether some inescapable sunk costs should be included, the consensus seems to be that the appropriate cost measure when cost is not measured on a firmwide basis should encapsulate the additional costs incurred by the dominant firm to increase output in order to lower prices. The cost measure should reflect the incremental costs incurred by the dominant firm to raise output. The costs incurred on the production of the inframarginal output should be excluded. This makes sense if what we are concerned with is the below-cost price cutting that may drive out rivals or forestall entry. The appropriate cost measure should reflect the costs incurred in making this price cut possible.

A similar logic that applied to the identification of the appropriate price applies equally here. The key is to identify what the European Commission calls the "relevant range,"²¹⁷ or the marginal customer or sales. The appropriate cost measure is the cost incurred in supplying the marginal customers to whom (allegedly) below-cost prices are offered. To better understand who the marginal customers are for the dominant firm, it may be

212. Areeda & Turner, *supra* note 149, at 703–04.

213. Elhauge, *supra* note 88, at 711.

214. *Id.* at 711–12.

215. *Id.* at 712.

216. *Id.* at 724–25.

217. Article 82 Guidance, *supra* note 167, at ¶ 41.

necessary to identify two groups of potential customers for the entrant: those who are currently the dominant firm's customers and those who are not.²¹⁸ The first group consists of existing customers of the dominant firm whom the entrant may target by undercutting the dominant firm's prices. Some of these customers would have been previously inframarginal customers who have now become contestable following market entry. The second group are those potential customers who are not attracted by the existing price-quality combination offered by the dominant firm but could be tempted by superior price-quality combinations. These customers would require a price lower than the lowest prevailing prices or quality higher than that offered by the dominant firm to choose the entrant's product. Otherwise, they would have purchased the dominant firm's product already. Absent a new competitive threat, the dominant firm may have decided that it would not be worthwhile to reduce prices further to attract these customers. In order to help it reach sufficient scale, the new entrant may target these customers by offering quality-adjusted prices that are even lower than the lowest prevailing price offered by the dominant firm.

To respond to an emerging competitive threat, the dominant firm may need to cut prices for both groups of customers. This may entail a price cut on the incremental output that it produces to grab market share preemptively from the new entrant to prevent the entrant from establishing a foothold and attaining the necessary scale,²¹⁹ and on the part of the existing output that has now become vulnerable as a result of the emergence of the competitive threat.

Under the logic of the incremental cost, the relevant cost measure would hence include the costs incurred in producing the additional output used to preempt the new entrant. These costs should not be exceedingly difficult to identify in the dominant firm's account books. The cost measure should also include the costs incurred to produce the output over which price cuts are now being offered by the dominant firm to retain existing customers. This naturally follows from the fact that the price used to conduct the price-cost comparison are the average price offered to all customers who are susceptible to the new entrant's product. The price offered and the costs incurred to produce for the same group of customers should be used for the price-cost comparison.

The difficulty, however, lies in isolating the costs incurred in producing

218. This discussion assumes that each customer purchases one unit of the product from one seller. If customers purchase varying quantities of the product and can do so simultaneously from multiple sellers, sales will not be counted on a per-customer basis but instead on a per-unit basis.

219. Elhauge, *supra* note 88, at 782.

the part of the existing output over which price cuts are offered. These units were not produced as one clearly identifiable increment. They were produced as part of the market-wide output prior to market entry. It could be difficult to identify the costs involved in producing those precise units. The only compromise solution would seem to be to use the AVC for the pre-entry market-wide output as the cost for those existing units. Therefore, with the possibility of algorithmic targeting, the appropriate cost measure would include both the incremental costs for producing the additional output to preempt the new entrant and the AVC for producing the existing units over which price cuts are offered.

However, such an approach might still face some practical problems. The first relates to the delineation of the predation period. As Elhauge pointed out, fixed and variable costs need to be determined with reference to the period of alleged predation.²²⁰ The line between fixed and variable costs could already be murky in traditional situations.²²¹ These costs may become even more difficult to distinguish once algorithmic targeting is possible, which may significantly complicate the delineation of the predation period. The firm may not even know when or which of the prices was set by the algorithm at a predatory level and which was not. The algorithm could start charging predatory prices right from the start, or it may take time to learn to set such prices.

Similar problems exist with regard to the end of the predation period. The price charged may not stay constant during the predation period and may fluctuate between a predatory price and a non-predatory one. If the algorithm regularly shifts the price between predatory and non-predatory levels, the end of predation would be difficult to establish. It is not clear whether the predation period only ends when the algorithm has stopped charging such prices for an extended period, the algorithm has been shut down, or the company stops the use of the algorithm in light of allegations of predation.

Second, algorithmic targeting would raise issues with respect to the definition of incremental costs. AIC typically includes product research, development, and marketing costs incurred with respect to the predatory units. As algorithmic predation is made possible by algorithmic targeting, an argument can be made that the costs of data collection and the use and development of the algorithm should be part of the AIC. A counter-argument, however, can also be made that these costs are not directly associated with the incremental units implicated in predation and would not count as incremental costs under the conventional understanding of the term.

220. *Id.* at 724–25.

221. Hovenkamp, *supra* note 188, at 4.

AAC may avoid this problem, as the costs of data collection and implementation of the algorithm probably would not be avoided had the predatory increment of sales not been produced. Data would have been collected and pricing algorithms put in place regardless of predation.

IV. ALGORITHMIC TARGETING AND ANTICOMPETITIVE REBATES

Algorithmic targeting can also be used in the context of rebates, which creates similar problems. The EU has a relatively more developed jurisprudence on rebates as compared to the United States. The EU rules on rebates are, at their core, about the burden of proof. Under EU antitrust law, we may distinguish three different types or categories of rebates that are treated differently by the law. On one end of the spectrum are quantitative rebates, which are applied across the board to every increase in sales.²²² These are treated favorably by the law. On the other end of the spectrum are fidelity or loyalty rebates,²²³ which are (rebuttably) presumed to be abusive.²²⁴ Then there are “[r]ebates falling within the third category,”²²⁵ as the EU General Court in *Intel* called other forms of rebates. This category is not subject to a presumption. In *Intel*, the General Court held that such rebates, where they are incapable of foreclosing competition, are compatible with Article 102.²²⁶ The Court of Justice expanded upon this finding, clarifying that rebates of the third category need to be examined in detail in individual cases to establish whether they are capable of foreclosing rivals.²²⁷ The court, however, stopped short of requiring actual proof of foreclosure.²²⁸

The European Commission’s Guidance Paper²²⁹ focuses on whether the rebate is conditional and has a foreclosure effect.²³⁰ In this assessment, the as-efficient competitor test plays a crucial role.²³¹ In general, the test follows the principles developed for predatory conduct. The Commission identifies

222. ALISON JONES ET AL., *EU COMPETITION LAW: TEXT, CASES, AND MATERIALS* 449–50 (7th ed. 2019).

223. In other words, these are rebates that are conditioned on exclusively buying from the dominant firm.

224. Case C-85/76, *Hoffmann-La Roche & Co. v. Comm’n of the Eur. Cmtys.*, 1979 E.C.R. 461, ¶¶ 89–90.

225. Case T-286/09, *Intel Corp. v. Eur. Comm’n*, ECLI:EU:T:2014:547, ¶ 78 (June 12, 2014).

226. *Id.* at ¶¶ 74–78.

227. See *Intel Corp.*, C-413/14 P, ¶¶ 129–47; see also *Post Danmark*, C-23/14, ¶ 27.

228. *Intel Corp.*, C-413/14 P, ¶¶ 129–47.

229. Article 82 Guidance, *supra* note 167.

230. *Id.* at ¶¶ 37–45.

231. See *Intel Corp.*, ECLI:EU:C:2017:632 at ¶¶ 138–47; Article 82 Guidance, *supra* note 167, at ¶¶ 39–45.

the “relevant range”²³² and examines whether the prices are above the LRAIC, below the LRAIC but above the AAC, or below the AAC.²³³ When rebates are above the LRAIC, foreclosure effects are unlikely, whereas rebates below the AAC have the capability of foreclosing equally efficient competitors. Between the LRAIC and the AAC, the Commission will look at other factors to determine whether equally efficient competitors will be excluded, in particular whether and to what extent competitors have realistic and effective counterstrategies at their disposal, for instance their capacity to also use a “non-contestable” portion of their buyers’ demand as leverage to decrease the price for the relevant range. Where competitors do not have such counterstrategies at their disposal, the Commission will consider that the rebate scheme is capable of foreclosing equally efficient competitors.²³⁴

Thus, the observations made above equally apply to rebates. It is worth highlighting two things. First, where the price is between LRAIC and AAC, the availability of counterstrategies becomes particularly important. As highlighted before, the questions of whether the competitor faces inframarginal customers and can use profits made from them to cross-subsidize the discounts offers to the marginal customers, and what is the contestable range cannot be answered without regard to algorithmic targeting. It is not sufficient to show that the dominant firm can make profits from the inframarginal customers, which can then be used for cross-subsidization. Where the competitor does not have the same ability to engage in algorithmic targeting, it will not be able to compete. The dominant firm would be able to offer a discount only on those sales that are truly marginal/contestable. A competitor without this ability will have to lower its price across the board. Thus, the costs for the competitor to counter the algorithmically targeted rebates will be higher than those for the dominant firm to implement those rebates in the first place. This raises critical questions about the as-efficient competitor test, for example, whether equal algorithmic targeting abilities should be assumed on the part of the competitor.²³⁵ A more detailed discussion of the impact of algorithmic targeting on the as-efficient competitor test will be deferred to Section VI.

Second, it should be emphasized once again that it might be extremely difficult to determine the “relevant range” over which costs are calculated. The Commission’s approach of identifying the “‘contestable share’ or ‘contestable portion’”²³⁶ faces the same problems as those that have been

232. Article 82 Guidance, *supra* note 167, at ¶¶ 43–44.

233. *Id.* at ¶ 44.

234. *Id.* at ¶ 44.

235. On the challenges with regard to the as-efficient competitor test, see *infra* Part VI.

236. Article 82 Guidance, *supra* note 167, at ¶ 42.

highlighted in the context of algorithmic predation. If the algorithm only targets marginal sales, it is difficult to determine the temporal start and end point for this assessment.

V. ALGORITHMIC TARGETING AND TYING AND BUNDLING

Unsurprisingly, the implications of algorithmic targeting would not be limited to predation and rebates but extend to the analysis of tying and bundling. In the future, a firm intent on pursuing a tie may be able to make use of algorithms to differentiate between the inframarginal customers who are willing to accept the tie and the marginal customers who will defect to a competing tying product when offered a tie. This newfound ability to differentiate customers will render tying a more effective and powerful tool.

A. *Tying in the Pre-digital World*

When a firm imposes a tie, it faces two types of customers. The first type are inframarginal customers for whom the additional consumer surplus from a rival's tied product over the tying firm's tied product is outweighed by the additional consumer surplus from the tying firm's tying product over a rival's tying product.²³⁷ This type of customers will accept the tie from the tying firm.²³⁸ This could be because they do not have a strong preference regarding the tied product, or because their preference for a rival's tied product is outweighed by their yet stronger preference for the tying firm's tying product. The second type are marginal customers for whom the consumer surplus from a rival's tied product over the tying firm's tied product outweighs the incremental consumer surplus from the tying firm's tying product over a rival's tying product.²³⁹ These customers will balk at being forced to take the tying firm's tied product.²⁴⁰ They will reject the tie and purchase both the tying and the tied products elsewhere.

A firm's decision to tie or not can be conceptualized at both the short-run static level and the long-run dynamic level. In the short run, the tying firm benefits mostly by being able to engage in price discrimination, in

237. Meyer L. Burstein, *The Economics of Tie-In Sales*, 42 REV. ECON. & STAT. 68, 69 (1960).

238. Frank Mathewson & Ralph Winter, *Tying as a Response to Demand Uncertainty*, 28 RAND J. ECON. 566, 573 (1997).

239. Burstein, *supra* note 237, at 69.

240. Mathewson & Winter, *supra* note 238, at 573.

particular, by means of a variable-proportions tie.²⁴¹ In the long run, the tying firm hopes to benefit from foreclosure of rivals, either by gaining market power in the tied product market through offensive leveraging or by protecting its market position in the tying product market through defensive leveraging.²⁴²

At the static level, the tying firm faces a trade-off between the profits that it stands to lose from the defection of the marginal customers and the additional profits it gains from the inframarginal customers. The tying firm reaps extra profits from the latter through price discrimination, especially by what has been called intra-product price discrimination, under which a variable-proportions tie is used as a metering device.²⁴³ Through such a tie, the tying firm can extract extra consumer surplus from customers who place particularly high valuation on the tying product.²⁴⁴ At the dynamic level, the benefits of tying consist of the extra profit the tying firm may make from its stronger market position in the tied product market or the profit which it manages to hang on to by successfully protecting its market position in the tying product market. The costs of a tie remain the same; they consist of the loss of profits when marginal customers defect to a competitor's tying product.

When a firm decides whether to impose a tie, it weighs the aforementioned trade-off in the short run and the long run. If the main impetus of a tie is price discrimination, the tying firm weighs the gains from the extraction of additional consumer surplus against the loss of profits from the marginal customers who defect to competing products. The firm will impose a tie if the gains outweigh the loss. If leveraging and foreclosure are the motivation behind the tie, the firm will impose a tie if the gains from leveraging outweigh the loss of profits from the defection of marginal customers. The potential loss of profits from customer defection is the main deterrent against a tie. In general, the stronger the firm's market power in the tying product market, the greater the value customers attach to the tying

241. Erik Hovenkamp & Herbert Hovenkamp, *Tying Arrangements and Antitrust Harm*, 52 ARIZ. L. REV. 925, 928–29 (2010).

242. See Michael D. Whinston, *Tying, Foreclosure, and Exclusion*, 80 AM. ECON. REV. 837 (1990); Barry Nalebuff, *Bundling as an Entry Barrier*, 119 Q.J. ECON. 159 (2004); Jay Pil Choi & Christodoulos Stefanadis, *Tying, Investment, and the Dynamic Leverage Theory*, 32 RAND J. ECON. 52 (2001); Jay Pil Choi, *Preemptive R&D, Rent Dissipation, and the "Leverage Theory"*, 111 Q.J. ECON. 1153 (1996).

243. Ward S. Bowman Jr., *Tying Arrangements and the Leverage Problem*, 67 YALE L.J. 19, 23–24 (1957).

244. Nicholas Economides, *Tying, Bundling, and Loyalty/Requirement Rebates*, in RESEARCH HANDBOOK ON THE ECONOMICS OF ANTITRUST LAW 121, 125–26 (Einer Elhauge ed., 2012).

firm's tying product.²⁴⁵ Fewer customers would reject the tie and the potential loss of profits will be smaller.

All else equal, a firm with greater market power in the tying product market will be in a better position to pursue a tie, and the tie will be more likely to be successful. This is why both the United States and the EU only condemn ties implemented by firms with a sufficient degree of market power in the tying product market. In the United States, under the *Jefferson Parish* case, the qualified *per se* rule is highly unlikely to apply to tying so long as the tying firm has less than a 30% market share in the tying product market.²⁴⁶ The Rule of Reason would apply in such case.²⁴⁷ In the EU, tying and bundling are regulated as abuse of dominance, which generally requires a market share of around forty percent.²⁴⁸ Currently, the European Commission uses a predation-based test for its assessment of the exclusionary effect of such behavior.²⁴⁹ It uses the incremental price²⁵⁰ paid for each product of the dominant firm. It assesses whether the price of both products in the bundle are above or below the dominant firm's LRAIC.²⁵¹ The European Commission normally will refrain from intervening when the price is above LRAIC because, in that case, an as-efficient competitor producing only one product should be able to compete profitably with the bundle.²⁵²

B. Tying in the World of Algorithmic Targeting

Algorithmic targeting would change the calculus facing a tying firm and the implementation of ties in some fundamental ways.

1. Tying Feasible at Lower Level of Market Power

First and foremost, it would greatly alleviate the most fundamental trade-off confronting a tying firm: the choice between the extra profit made from increased sales of the tied product and the profit loss from reduced sales of the tying product.²⁵³ The acuity of this trade-off varies depending on the

245. HERBERT HOVENKAMP, FEDERAL ANTITRUST POLICY: THE LAW OF COMPETITION AND ITS PRACTICE 89 (4th ed. 2011).

246. *Jefferson Parish Hosp. Dist. No. 2 v. Hyde*, 466 U.S. 2, 26–27 (1984).

247. *Id.* at 29.

248. JONES ET AL., *supra* note 222, at 337.

249. Article 82 Guidance, *supra* note 167, at ¶¶ 59–61.

250. Where possible, incremental costs will be used.

251. Article 82 Guidance, *supra* note 167, at ¶ 60.

252. *Id.*

253. On this trade-off see *supra* text to notes 242–245.

feasibility of the selective imposition of ties, which has been shown to be feasible in some circumstances.²⁵⁴ In situations where such selective imposition is impossible, perhaps because a tying firm has difficulty distinguishing between inframarginal and marginal customers, it will need to impose the tie uniformly. The trade-off could limit the firm's willingness to pursue a tie.

Algorithmic targeting softens this trade-off and renders selective ties much more practical by allowing the tying firm to differentiate its customers.²⁵⁵ Once customers can be more easily segregated, the tie can be selectively imposed on the inframarginal customers, who are most susceptible to a tie. The marginal customers can be allowed to continue to purchase the tying and the tied products separately or can be offered substantial bundled discounts. The tying firm avoids or at least minimizes the loss of profits from customer defection. In fact, profits from the inframarginal customers can be used to subsidize the bundled discounts offered to the marginal customers. The major deterrent against tying is now removed. A tie would still remain profitable for the tying firm even if a significant number of its customers are marginal, so long as there is some profit to be made by compelling the inframarginal customers to purchase the bundle. The clear implication is that a tie can be implemented at a considerably lower level of market power in the tying product market. Whether a tie is ultimately illegal still requires a showing of foreclosure effects. But what is clear is that a firm can implement a tie feasibly at a lower market share.

2. Facilitation of Offensive Leveraging

Algorithmic targeting would also make foreclosure of rivals easier, turning offensive leveraging into a more credible strategy. The most frequently mentioned competitive harm for tying is foreclosure in the tied product market. Even Ward Bowman, one of the most strident defenders of tying as a business practice, concedes that the conception of the Clayton Act is premised on the notion of leverage and foreclosure.²⁵⁶ Offensive leveraging refers to when a firm that possesses significant market power in the tying product market leverages that power to gain a competitive advantage in the tied product market.²⁵⁷ Rivals in the tied product market are

254. Leslie, *supra* note 41, at 784 (noting that “[s]ellers often selectively impose their tying requirements” and discussing examples).

255. ALGORITHMS, *supra* note 89, at 9.

256. Bowman, Jr., *supra* note 243, at 30.

257. Whinston, *supra* note 242, at 837, 853–54.

thus foreclosed, either as significantly weakened competitive forces or completely driven out of the market.

Economists have proposed various models for offensive leveraging, some static and some more dynamic in nature.²⁵⁸ Algorithmic targeting would seem to have a greater role to play in the static models. It would generally render tying a more effective tool for offensive leveraging. This is accomplished in three main ways.

First, it would turn tying into a less costly and more profitable strategy for the tying firm. Algorithmic targeting would allow the tying firm to maintain substantial sales of the tied product and take market share from rivals without lowering prices for the tied product across the board. Price cuts can be selectively targeted at customers who have a low valuation of the tied product. The ability to distinguish the marginal from the inframarginal customers is key to the success of foreclosure in a number of economic models.²⁵⁹

Second, algorithmic targeting would allow the tying firm to more effectively deny rivals the market share necessary for attaining economies of scale. Tying can hurt a new entrant by making it difficult for the entrant to capture market share.²⁶⁰ The tying firm may attempt to hold on to market share by offering bundled discounts to marginal customers so that customers eschew the entrant's tied product.²⁶¹ Tying thus achieves foreclosure by leaving entrants with insufficient scale to make entry viable.²⁶² A tying firm's ability to capture market share is contingent on its ability to entice customers with bundled discounts.²⁶³ Once algorithmic targeting is possible, the firm can tailor the discounts according to the customer's valuation of the bundle as opposed to offering one across-the-board discount that will inevitably result in the loss of some low-valuation customers. More targeted pricing strategies would allow the firm to hang on to more customers, hence leaving even fewer of them to the new entrant. The new entrant would be even more hard-pressed than otherwise to achieve sufficient scale and can be more easily foreclosed. Moreover, as mentioned earlier, algorithmic targeting turns cross-subsidization into a feasible strategy. The targeted discounts

258. The models of Michael Whinston, *supra* note 242, and Barry Nalebuff, *supra* note 242, are both static, whereas the two models by Jay Pil Choi, *supra* note 242, are dynamic in nature and are premised on innovation.

259. Dennis W. Carlton & Michael Waldman, *Robert Bork's Contributions to Antitrust Perspectives on Tying Behavior*, 57 J.L. & ECON. 121, 216 (2014); Nalebuff, *supra* note 242, at 168.

260. Nalebuff, *supra* note 242, at 165.

261. *Id.* at 169–70.

262. *Id.* at 163.

263. *Id.* at 170.

offered to the marginal customers can be cross-subsidized by the extra profits from the inframarginal customers subject to the tie.

Third, algorithmic targeting would make tying a more effective offensive weapon by rendering the threat of tying more credible. In one of the most influential economic models of offensive leveraging, Michael Whinston puts forward a relatively stylized account of tying that is premised on a credible pre-commitment to tie.²⁶⁴ The credibility of the commitment is important because once entry has occurred, the rational strategy for the incumbent is to accommodate the entrant by lowering output and abstaining from tying.²⁶⁵ The incumbent foregoes profits from sales in the tying product market when pursuing a tie.²⁶⁶ Therefore, the incumbent would never commit to tie unless it was sure that it could force the rival out of the tied product market, which would raise the incumbent's profits unless a sufficient number of customers have a low valuation of the tying product and choose to abandon the product instead of accepting the tie.²⁶⁷

Once the incumbent has committed to tie, however, it can only continue to enjoy monopoly profits from the tying product if it also makes substantial sales of the tied product, which requires the incumbent to cut prices and take significant market share from rivals.²⁶⁸ Whinston suggests that a pre-commitment to tie could be made through product design or adjustments to the production process, both of which entail significant sunk costs.²⁶⁹ Without a credible pre-commitment, the threat to tie would lack credibility and would fail to deter rivals as "any equilibrium outcome will be equivalent to one where only independent pricing is allowed."²⁷⁰

With algorithmic targeting, the tying firm would be able to minimize lost sales in the tying product market because it can apply the tie selectively only to the inframarginal customers who have a high valuation of the tying product. Low-valuation customers would be spared the tie. The minimization of loss of profits would mean that tying is a more plausible strategy even absent a credible pre-commitment to tie. A tying firm would no longer need to pursue costly actions such as product redesigns or changes in the production process to signal its intention to tie. Tying would hence become a more flexible and potent tool for offensive leveraging, which should increase the likelihood that tying is used to achieve foreclosure and augment

264. Whinston, *supra* note 242, at 839–40.

265. Nalebuff, *supra* note 242, at 163.

266. Whinston, *supra* note 242, at 844.

267. *Id.* at 844–45.

268. *Id.* at 840.

269. *Id.* at 839.

270. *Id.* at 840.

the anticompetitive potential of tying.

3. Variable-proportions Ties No Longer Needed to Accomplish Price Discrimination

Once algorithmic targeting is possible, price discrimination would become a much less persuasive justification for variable-proportions ties. Under this type of tie, the tying and the tied products are used in variable-proportions, with high-intensity users of the tying product consuming more of the tied product together with the tying product.²⁷¹ The quintessential example is printers and replacement ink cartridges.²⁷² The seller of the tying product, however, is unable to distinguish between high-intensity and low-intensity users and vary its prices accordingly.²⁷³ If the intensity of use of the tying product is reflected in the consumption of a complementary product, the seller can tailor its pricing according to intensity of use by way of a variable-proportions tie.²⁷⁴ The seller can tie the sale of the tying product to the sale of a tied product at supra-competitive prices.²⁷⁵ Price discrimination is accomplished when high-intensity users of the tying product end up paying a higher price for the overall bundle than do low-intensity users. In this kind of intra-product price discrimination, tying plays a critical role because the seller is unable to practice price discrimination directly. Herbert and Erik Hovenkamp have argued that the kind of second-degree price discrimination made possible by variable-proportions ties is most probably welfare-enhancing.²⁷⁶ The possibility of price discrimination is thus often used as a procompetitive justification for tying.

Algorithmic targeting would render variable-proportions ties a redundant tool for price discrimination. Firms need to rely on tying to price discriminate because they are unable to distinguish between high-intensity and low-intensity users of the tying product and cannot prevent arbitrage. In the future, algorithms may alleviate the first problem by helping firms to differentiate customers and charge them different prices.²⁷⁷ Direct price discrimination may become possible with algorithm targeting, obviating the need to resort to a tie. Firms may be able to draw finer distinctions than

271. Bowman, Jr., *supra* note 243, at 23–24.

272. Einer Elhauge, *Tying, Bundled Discounts, and the Death of the Single Monopoly Profit Theory*, 123 HARV. L. REV. 397, 404 (2009).

273. Bowman, Jr., *supra* note 243, at 23.

274. *Id.* at 23–24.

275. *Id.* at 24.

276. Hovenkamp & Hovenkamp, *supra* note 241, at 928–29.

277. ALGORITHMS, *supra* note 89, at 9.

simply high- and low-intensity, and tailor their prices in accordance with gradations of intensity of use. There should be no loss in the precision of price discrimination when it is pursued directly rather than through a tie.

Algorithmic targeting would not rule out price discrimination as a justification for tying entirely; it is not clear whether algorithms would also render ties redundant for the purpose of intra-consumer and inter-product price discrimination.²⁷⁸ Intra-product price discrimination, however, is the overriding justification for variable-proportions ties, which account for a significant proportion of price-discriminating ties. The fact that ties are no longer necessary for achieving intra-consumer price discrimination means that tying loses one of its main justifications.

To sum up, algorithmic targeting would allow tying to be pursued at a lower level of market power, would render much less persuasive a commonly invoked justification for tying, and would make offensive leveraging more attainable through a tie. More stringent scrutiny of tying may be justified where algorithmic targeting is incorporated into tying practices with increasing regularity.

VI. ALGORITHMIC TARGETING AND THE AS-EFFICIENT COMPETITOR TEST

We should briefly consider what these findings might mean for the as-efficient competitor test. In the EU as well as the United States, the as-efficient competitor is an important benchmark in assessing exclusionary conduct.²⁷⁹ As mentioned earlier, the EU approach to predation as well as rebates, and tying and bundling strongly relies on the as-efficient competitor test.²⁸⁰ Since the *Intel* judgment, some even see it as the central theme of the EU's abuse of dominance prohibition, protecting only efficient competitors.²⁸¹ The importance of the as-efficient competitor test stems from

278. See George J. Stigler, *United States v. Loew's Inc.: A Note on Block-Booking*, 1963 SUP. CT. REV. 152, 152–57 (1963) (illustrating intra-consumer price discrimination); Burstein, *supra* note 237 (illustrating inter-product price discrimination).

279. Cf. Miroslava Marinova, *What Can We Learn About the Application of the As-Efficient Competitor Test in Fidelity Rebate Cases from the Recent Us Case Law?*, 41 WORLD COMPETITION 523, 523 (2018) (discussing rebates); Article 82 Guidance, *supra* note 167, at ¶ 67 (using as as-efficient competitor to determine any kind of anticompetitive foreclosure); A. Douglas Melamed, *Exclusive Dealing Agreements and Other Exclusionary Conduct—Are There Unifying Principles?*, 73 ANTITRUST L.J. 375 (2006) (exploring different tests); Richard A. Posner, *Exclusionary Practices and the Antitrust Laws*, U. CHI. L. REV. 506, 519 (1974); RICHARD A. POSNER, ANTITRUST LAW 194 (2001).

280. Article 82 Guidance, *supra* note 167, at ¶ 47–61.

281. Pablo Ibáñez Colomo, *The Future of Article 102 TFEU After Intel*, 9 J. EUR. COMPETITION L. & PRAC. 293, 294 (2018).

its predictability as applied in concrete cases. As such, the dominant firm only needs to examine its own costs to determine whether it could or could not compete under the conditions it aims to offer to its competitor. Similarly, competition authorities are provided with a clear benchmark. They only need to find out the cost structure of the dominant firm to perform the test.

However, the guidance offered by the dominant firm's costs can be murky in practice. For example, it is unclear which costs need to be examined in cases involving product differentiation or two-sided markets.²⁸² For instance, it seems to make little sense to apply a cost-based test only to the "free" side of a two-sided platform market where the platform offers "free" products to customers. The platform's behavior makes economic sense when the revenue-generating side makes up for the "profit loss" on the free side.²⁸³ Tests such as the profit sacrifice test or the no-economic sense test are suggested as a remedy.²⁸⁴ These tests can be applied to help determine whether there is evidence of foreclosure by way of a strategy that requires the foreclosure to be profitable and the corresponding evidence of intent.

Similarly, in the case of algorithmic predation and exclusion, questions about establishing the relevant cost in the concrete case might arise so that the profit sacrifice test or the no-economic sense test might come into play. As a first step we may question whether "as-efficient" in this context means only "as-efficient" in producing the individual good, or whether it also includes the ability to identify marginal customers and engage in algorithmic targeting. Although we might argue that such an ability should be taken into account because the ability to identify and price discriminate would have substantial effects on costs, this leaves some complex questions unanswered. First, as we have explained in detail above, it is difficult to determine which costs should be used when the dominant firm is able to engage in algorithmic targeting.

Second, as in the case of two-sided markets, it would seem to make economic sense to offer the low price as long as the loss in revenue can be offset by another group of customers. A compounding factor in the case of algorithmic predation and exclusion are the well-known problems that result

282. Kai-Uwe Kuhn & Miroslava Marinova, *The Role of the As-Efficient-Competitor After the CJEU Judgment in Intel*, 4 COMPETITION L. & POL'Y DEBATE 64, 65 (2018).

283. Friso Bostoen, *Online Platforms and Pricing: Adapting Abuse of Dominance Assessments to the Economic Reality of Free Products*, 35 COMPUT. L. AND SEC. REV. 263, 268 (2019) (explaining how platforms need to balance the income made on one side with the cost incurred on the other, a form or cross-subsidization).

284. Kuhn & Marinova, *supra* note 282, at 68.

from the amalgamation of data troves.²⁸⁵ The question in this regard relates to tipping and whether a competitor that later enters the market will ever be able to be as-efficient as the incumbent, who is already in possession of the algorithm and the relevant data pool to discriminate between marginal and inframarginal customers. In the case of algorithmic predation and exclusion, the problem might be even more pronounced, as only the availability of this kind of data allows such targeted offers. Does it make sense to insist that the protection of abuse of dominance laws only be extended to as-efficient competitors when a new entrant can never be as-efficient?

These issues seem to go to the heart of competition policy. Should antitrust law protect less efficient competitors? How should efficiency be assessed? Do we need to entertain the idea of protecting the less efficient competitor in such cases, as not doing so will lead to entrenching market power because data advantages make it virtually impossible to compete with the dominant firm?²⁸⁶ Would a competition policy approach that allows/encourages such behavior not ultimately lead to an economy which consists only of monopolized markets?

VII. CONCLUSION

The challenges posed by algorithmic targeting to the analysis of predatory and exclusionary conduct are probably only the opening chapter of a long-running narrative of adaptations made by antitrust law to the emergence and popularization of artificial intelligence. In this paper, we have explained what algorithmic targeting is and explored a case study that shows how such targeting is already pursued today while highlighting the current state of pricing algorithms. The future challenge is that, with sufficient data and sophisticated algorithms, it may be possible to target price cuts only to

285. On the problems of data troves, see, for example, JACQUES CREMER, YVES-ALEXANDRE DE MONTJOYE & HEIKE SCHWEITZER, EUROPEAN COMM'N, COMPETITION POLICY FOR THE DIGITAL ERA: REPORT OF THE EUROPEAN COMMISSION 108, 110 (2019), <https://data.europa.eu/doi/10.2763/407537> [<https://perma.cc/8AWS-J3KU>]; HM TREASURY, UNLOCKING DIGITAL COMPETITION: REPORT OF THE DIGITAL COMPETITION EXPERT PANEL FOR THE UK TREASURY (2019), https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/785547/unlocking_digital_competition_furman_review_web.pdf [<https://perma.cc/BZV8-YMPA>]; MINISTRY OF ECON., TRADE & INDUS., FUNDAMENTAL PRINCIPLES FOR RULE MAKING TO ADDRESS THE RISE OF PLATFORM BUSINESSES ¶ 2(4) (2018), https://www.jftc.go.jp/en/policy_enforcement/survey/index_files/190220.1.pdf [<https://perma.cc/H6CX-EFZ8>] (Japan); L'AUTORITÉ DE LA CONCURRENCE & BUNDESKARTELLAMT, COMPETITION LAW AND DATA: JOINT REPORT BY THE GERMAN AND FRENCH COMPETITION AUTHORITY 16 (2016).

286. See, e.g., Kuhn & Marinova, *supra* note 282, at 63 (regarding significant economies of scale and/or scope).

the marginal customers while leaving the prices for the inframarginal customers untouched. Some even argue that this is already feasible. We then showed how this ability challenges fundamental assumptions regarding predatory pricing, rebates, and tying and bundling. Subsequently, a closer analysis of the different elements of a predatory pricing claim, in particular recoupment and the different cost and price measures, showed how algorithmic targeting creates difficulties with regard to each of them. We also showed that similar challenges exist when employing the tests for rebates and tying and bundling. It is clear that artificial intelligence will continue to require us to revisit the fundamental assumptions about firm and consumer behavior that underpin many antitrust doctrines. As artificial intelligence and other related technology become more advanced, the interaction between firms and consumers will continue to evolve. It is imperative that antitrust laws keep up with the times and adapt to the rapidly changing technological landscape. This article is one modest contribution to this endeavor of paramount importance.