LUND UNIVERSITY LEGAL RESEARCH PAPER SERIES

LundLawCompWP 1/2022 Jan 2022

Algorithmic Predation and Exclusion

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Abstract:

The debate about the implications of algorithms on competition 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. This article seeks to fill the 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 US 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. This renders tying and bundling more feasible and effective for dominant firms.

JEL: L41

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1. I. INTRODUCTION

Virtual Competition by Ariel Ezrachi and Maurice Stucke[1] can be seen to have brought the attention of the competition law community to the issues of algorithms and big data.[2] 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 competition law should respond to the phenomenon. The discussion has ranged from the feasibility of algorithmic collusion to how should competition 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. Personalized pricing and precise identification of marginal customers with the help of algorithms and big data have greatly improved a dominant firm's ability to pursue predatory and exclusionary conduct. Before personalized pricing and precise customer identification were possible, a dominant firm must pursue predation and exclusionary conduct across the board in the market. This necessitates a tradeoff 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 and tying and bundling are structured in ways that implicitly reflect this tradeoff. As will be demonstrated in this article, specific targeting of customers made possible by the use of algorithms and big data, hereinafter referred to as algorithmic targeting, significantly reduces the acuteness of this tradeoff if not eliminates it altogether. Algorithmic targeting threatens to shake the foundations of these legal doctrines and may call for a fundamental rethink in the way competition law should analyze a range of predatory and exclusionary conduct. By way of example, personalized pricing allows the 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 US.

We first set out the central problems posed by algorithmic targeting by looking at a case study in an input market, Uber's Hell program. This exposition highlights the possibilities for personalized pricing and other forms of algorithmic targeting and sets out the basis for reconsidering the analysis of predation pricing, rebates, and tying and 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 ability to incorporate algorithmic targeting in personalized pricing, targeted rebates, and targeted implementation of ties poses much greater challenges to antitrust analysis of such conduct than is currently understood. Without trying to settle the debate, this article argues that the possibility of algorithmic targeting renders recoupment much more feasible. It significantly reduces the importance of the recoupment requirement, perhaps to the extent of redundancy in a number of cases. It also argues that the targeted implementation of ties minimizes the profit tradeoff facing a tying firm and reduces the minimum amount of

[1] ARIEL EZRACHI & MAURICE STUCKE, VIRTUAL COMPETITION (2016).

[2] See e.g., Francisco Beneke & Mark-Oliver Mackenrodt, *Remedies for Algorithmic Tacit Collusion*, 9 JOURNAL OF ANTITRUST ENFORCEMENT 152 (2021). Emilio Calvano et al., *Artificial Intelligence, Algorithmic Pricing, and Collusion*, 110 THE AMERICAN ECONOMIC REVIEW 3267 (2020). Marixenia Davilla, *Is Big Data a Different Kind of Animal? The Treatment of Big Data Under the EU Competition Rules*, 8 JOURNAL OF EUROPEAN COMPETITION LAW & PRACTICE 370 (2017). Michal S. Gal, *Algorithms as Illegal Agreements*, 34 BERKELEY TECHNOLOGY LAW JOURNAL 67 (2019). Karsten T. Hansen, Kanishka Misra & Mallesh M. Pai, *Frontiers: Algorithmic Collusion: Supra-competitive Prices via Independent Algorithms*, 40 MARKETING SCIENCE 1 (2021). Wolfgang Kerber, *Digital Markets, Data, and Privacy: Competition Law, Consumer Law and Data Protection*, 11 JOURNAL OF INTELLECTUAL PROPERTY LAW & PRACTICE 856 (2016). Ulrich Schwalbe, *Algorithms, Machine Learning, and Collusion*, 14 JOURNAL OF COMPETITION LAW & ECONOMICS 568 (2019). ALLEN P. GRUNES & STUCKE, MAURICE E., BIG DATA AND COMPETITION POLICY (2016). BEATA MÄIHÄNIEMI, COMPETITION LAW AND BIG DATA: IMPOSING ACCESS TO INFORMATION IN DIGITAL MARKETS (2020).

market power necessary to render tying exclusionary. This may require a fundamental rethink of the current legal standards as they are applied to algorithmic predation and exclusion.

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

In this section we show how the combination of algorithms with big data allow for companies to personalize their offers and how this might give rise to algorithmic 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 enact behavior that are *prima facie* predatory. In the second part, this section applies insights from the 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 personalize efforts to exclude competitors from input can be found in the case of Uber's Hell program.[3] Hell was a program run by Uber to target drivers that also drove for the 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.[4] 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 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.[5] One could also imagine that better prices were offered to these drivers.[6] All this happened without the drivers knowing that they were accorded 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 to achieve algorithmic exclusion. These were, however, only available to those drivers who could multi-home. In this sense, Uber's Hell program was aimed at allowing Uber to exclude a competitor from the input market. The tools were very targeted. They included personalized rebates or bonuses or personalized overbuying.[7] In the following we briefly explore these *potential* theories of harm using Uber's Hell program as a case study.[8]

The case of Hell concerns the provision of rebates or bonuses in the input market.[9] This can be compared to the EU *British Airways v Commission* case.[10] In that case, British Airways provided bonuses to upstream travel agents to incentivize them to sell more British Airways tickets. These bonuses had the effect of foreclosing competitors by making it more difficult for competitors to access consumers via travel agents.[11] In a similar way, Uber' personalized bonuses lock in the input (drivers) to the disadvantage of competing platforms. They reduce the availability of drivers for Uber's competitors.

[3] See Ignacio Herrera Anchustegui & Julian Nowag, *Buyer Power In The Big Data And Algorithm Driven World: The Uber & Lyft Example*, Sept. 2017 CPI ANTITRUST CHRONICLE 31 (2017).
[4] 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.
[5] Mariella Moon, *Uber's "Hell" program tracked and targeted Lyft drivers*, ENGADGET.COM, April 13, 2017, https://www.engadget.com/2017/04/13/uber-hell-program-lyft-drivers (last visited May 22, 2018).
[6] In the case of Uber this is done by lowering the fee that Uber charges the drivers.
[7] For more details on these theories in the context of Hell, see Anchustegui and Nowag, *supra* note 5.
[8] Without looking at the specifics to determine whether the Uber case would actually meet the criteria of exclusionary conduct.
[9] On such rebates (also called reverse rebates in general) and its relationship to buyer power, see IGNACIO HERRERA ANCHUSTEGUI, BUYER POWER IN EU COMPETITION LAW (2017).
[10] Case T-219/99 *British Airways v Commission* EU:T:2003:343 and Case C-95/04 P *British Airways v Commission* EU:C:2007:166.
[11] In those days travel agents were the main route to sell tickets to final consumers.

Where this leads to an overall reduction of drivers for the competitor it reduces its attractiveness to consumers. There are not many (legal)[12] 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) recruiting more drivers. In the first case the increase in cost is obvious. In the second case one could expect drivers to demand a premium for exclusivity. 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 a 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 can the cost increase be contained. This stems from the fact that Uber is able to target only the marginal drivers. Without algorithmic schemes that facilitate such targeting the competitor has 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.[13] The Hell program allowed Uber to steer its demand for drivers in such a way that it would hurt its competitors at the same time.

This idea of buying up a competitor's input is the basis for a second possible theory of harm: predatory bidding. The buyer aims to exclude its competitor by either buying more than it objectively needs or by paying a price above market value, or both.[14] In the US, *Weyerhaeuser*[15] applies the traditional predatory pricing test to predatory bidding. This test, which was first established *in Brooke Group*[16], means that a showing of pricing below cost alone is not enough. A dangerous likelihood of recoupment also needs to be shown. In *Weyerhaeuser*, the US Supreme Court used the predation test for predatory bidding, which it deems to follow the same logic of incurring a short-term loss to exclude a rival in the long term. In the opinion the court expressed a longstanding concern about the effectiveness of predation. Predation is rarely effective as new entrants might enter the market after the predation phase when prices are again at or even above the competitive level. If the predator can be prevented from raising prices to a supra-competitive level during the recoupment period, predation redounds overall consumer welfare gains. Thus, probable recoupment would need to be established to pursue Uber's Hell program under a predatory bidding claim in the US.

The use of big data and algorithms allows Uber to distinguish between those (marginal) drivers that might multi-home from those who are loyal to Uber. Thus, Uber did not have to pursue predation across the board but could do so in a targeted manner. The overall predation loss from such a strategy is much smaller than in a traditional case because Uber does not have had to offer the supra-competitive overbidding price to all drivers. Consequently, the profit required in the recoupment phase to make the predation worthwhile is also correspondingly much smaller. Moreover, given that the supra-competitive price is only paid to a small number of drivers, the firm can afford to offer an even higher price than when individual targeting is not feasible.

While 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*. A prime candidate that would be in a position to amass enough data for such targeting are Amazon or large supermarkets.[17] These firms are able to collect vast amounts of data on spending patterns and sales of its 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.[18] It has also supplied personalization technology to third-party sellers on its platform. Hotel booking websites are also known for making use of demographic data to engage in

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[12] The competitor could have mirrored the behaviour of Uber and collected the data from the Uber app illegally.

[13] 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.

[14] John B. Kirkwood, *Buyer Power and Exclusionary Conduct: Should Brooke Group Set the Standards for Buyer-Induced Price Discrimination and Predatory Bidding*, 72 ANTITRUST LAW JOURNAL 625 (2005). Steven C. Salop, *Anticompetitive Overbuying by Power Buyers*, 72 ANTITRUST LAW JOURNAL 669 (2005).

[15] Weyerhaeuser Co. v. Ross-Simmons Hardwood Lumber Co., 549 U.S. 312 (2007).

[16] Brooke Group Ltd. v. Brown & Williamson Tobacco Corp., 509 U.S. 209 (1993).

[17] 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 JOURNAL OF ANTITRUST ENFORCEMENT 203 (2018).

[18] Axel Gaultier, Ashwin Ittoo & Pieter Van Cleynenbreugel, *AI algorithms, price discrimination and collusion: a technological, economic and legal perspective*, 50 EUROPEAN JOURNAL OF LAW AND ECONOMICS 405, 408–09 (2020).

price discrimination.[19] Even Home Depot has reportedly been found to price discriminate.[20] 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 offline via Gmail accounts, for example.[21] 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 individualized pricing by algorithms using sophisticated machine learning has been confirmed by experimental studies.[22] A number of commentators such as Salil Mehra and Michal Gal have noted the enhanced ability of algorithms to engage in price discrimination.[23] A report by the Obama Administration highlighted the possible consumer harm that may flow from more precise price discrimination.[24] The OCED has also acknowledged the possibility of individualized pricing by algorithms and warned about the competition implications of such practice.[25] 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."[26]

This is not to say that there is unanimous consensus on the feasibility of individualized pricing. Some commentators have argued that it remains a theoretical possibility rather than a common reality.[27] Gal has argued that businesses could be deterred by consumer backlash and thwarted by consumer counter-measures in the pursuit of personalized pricing.[28] Therefore, technical feasibility does not necessarily turn it into a widespread phenomenon.

B. Other Forms of Targeted Exclusionary Conduct

From a technological point of view, the question is not the possibility of such targeting but rather its degree of precision, which is contingent on the availability of sufficient data.[29] There is no doubt that some form of price discrimination is already happening. It is more of a question of when rather than if. Even if the ability to practice finely tuned price discrimination is not widely held at this point, technological progress leaves little doubt that personalized pricing could very well be a reality in the future. More importantly, as will be explained subsequently, the analysis and conclusions offered in this article are not premised on the ability to practice personalized pricing. The ability to distinguish marginal from inframarginal customers, which 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

As already observed in the example of Uber's Hell program, algorithmic targeting in pursuit of predation is possible as long as there is sufficient data. Once a dominant undertaking has identified the marginal sales to its customers with an algorithm, it can easily reduce the price it charges on these sales. More targeted price cutting helps 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 means 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 is on the need to prove likelihood of recoupment, with likelihood

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[19] *Id.* at 409.
[20] *Id.* at 409.
[21] 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, https://www.cnbc.com/2019/05/17/google-gmail-tracks-purchase-history-how-to-delete-it.html (last visited May 22, 2019).
[22] Gaultier, Ittoo, and Van Cleynenbreugel, *supra* note 20 at 415.
[23] Salil Mehra, *Price Discrimination-Driven Algorithmic Collusion: Platforms for Durable Cartels*, 26 STANFORD JOURNAL OF LAW, BUSINESS & FINANCE 171, 175 (2021).
[24] *Id.* at 180.
[25] OECD, *Algorithms and Collusion: Competition Policy in the Digital Age* 16 (2017), www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm (last visited Jul 19, 2021).
[26] Terrell McSweeney & O'Dea Brian, *The Implications of Algorithmic Pricing for Coordinated Effects Analysis and Price Discrimination Markets in Antitrust Enforcement*, 32 ANTITRUST 75, 77 (2017).
[27] Gaultier, Ittoo, and Van Cleynenbreugel, *supra* note 20 at 415.
[28] Gal, *supra* note 4 at 92.
[29] For an overview with regards to the benefits for collecting data from numerous sources see David Martens et al., *Mining massive fine-grained behavior data to improve predictive analytics*, 40 MIS QUARTERLY ARCHIVE 869 (2016).

of recoupment not a required element for predatory pricing under EU law. Algorithmic targeting may necessitate the reexamination of the recoupment requirement under US law and bolster the EU position in this debate.

The possibility of personalized pricing also an has 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 this purpose. Whether these cost measures are still appropriate in light of algorithmic targeting becomes a valid question which will also be examined in the next section.[30]

2. Rebates

As the Hell example demonstrates, algorithmic targeting also renders the use of rebates much more precise. A similar cost-based approach as 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*[31] or an individualized basis, that is to say a different discount for each customer, as in the EU *Intel* case.[32]

The use of algorithms makes possible a new form of rebates. These rebates obviate the need for individual calculations and negotiations. They 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. Individual 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 number of customers.

Algorithmically targeted rebates kill two birds with one stone. They are cheaper to implement than are individualized rebates but simultaneously can be implemented across large groups of customers as standardized rebates. Algorithms improve the effectiveness of rebates by allowing for better targeting across a large group of customers. In particular, with these techniques it is possible to identify the contestable sale unit. It becomes possible to identify individual transactions over which competition exists and adjust the price accordingly. Discounts can 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.[33] One may distinguish between *pure* and *mixed bundling*.[34] 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 US.

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 affects 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.[35]

Algorithmic targeting allows 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. The revenue gained from the tie can then be used to offer bundled discounts to customers with an elastic demand at a price lower than that of

[30] See below section III.
[31] Case C-23/14 *Post Danmark* ECLI:EU:C:2015:651.
[32] Case C-413/14 P *Intel v Commission* ECLI:EU:C:2017:632.
[33] In the EU classical examples are Case 22/78 *Hugin Kassaregister AB v Commission* ECLI:EU:C:1979:138; Case T-83/91 *Tetra Pak International SA v Commission* ECLI:EU:T:1994:246; Case T-30/89 *Hilti AG v Commission* ECLI:EU:T:1991:70; Case T-201/04 *Microsoft Corp. v Commission* ECLI:EU:T:2007:289, in the US e.g. Eastman Kodak Co. v. Image Technical Servs., Inc., 504 U.S. 451 (1992).
[34] ROGER J. VAN DEN BERGH, COMPARATIVE COMPETITION LAW AND ECONOMICS 316–17 (2017).
[35] Ibid.

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 can be successfully employed at a lower level of market power.

4. The Core Challenges of Algorithmic Targeting

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

First, some of the general assumptions about these practices need to be questioned. For example, in predation cases, it is traditionally asked how a firm can afford below-cost pricing[36] and whether the predation loss can be recouped.[37] Algorithms allow firms to target their price cutting. Thus, only marginal customers receive the "benefit" of below-cost pricing whether in form of a lower price, rebates or a discounted bundle. Depending on the data available, it might be even possible to determine the reservation price for a particular customer for an individual transaction. Such targeting also means that in-group cross-subsidization will be much more relevant. Price discrimination within a customer group makes possible predation, rebates, and bundling for the marginal customers paid for by the inframarginal customers. Below-cost pricing can be implemented without a substantial loss.

Cross-subsidization, however, is not the only way in which algorithmic targeting facilitates predatory and exclusionary behavior. The cost of predation and exclusionary conduct is dramatically reduced as the predatory price, the rebate, or the bundle is offered only to the select few customers and only for specific transactions. This reduction in costs completely changes the cost-benefit calculation.[38] The loss that needs to be recovered is much lower and the time frame for recovery (if any actual loss is incurred due to the cross-subsidization) is much shorter. Predatory or exclusionary conduct becomes more profitable and hence more probable for a dominant undertaking.[39]

Second, often neither the customers nor the competitors are aware that algorithmic targeting is possible. This is relevant for two reasons. First, if the customer knows that they have been classified as inframarginal they might have a chance to react. Strategic behavior on the part of the customer can 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.[40] Second, a competitor who does not engage in such 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.[41]

Before proceeding further in our discussion, it is important to clarify and emphasize that while this article speaks of personalized pricing and individual targeting by algorithms, the degree of price discrimination does not need to approach anything close to perfect for the ensuing analysis to apply. Perfect price discrimination is not required for a dominant firm to implement below-cost pricing or to charge supra-competitive prices during the recoupment period in a more targeted manner. All that is needed is for the dominant firm to be able to differentiate marginal customers from inframarginal ones. Customers within these two groups of customers may vary further in their price elasticities and the ability to draw finer distinctions between customers within each group will enhance a dominant firm's ability to engage in abusive conduct. Yet this enhanced ability to differentiate customers only affects the effectiveness of the conduct. The insights and conclusions that are drawn below are

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[36] In other words, a question of deep pocket of the predator and where they are derived from.
[37] With regard to Amazon, see Sussman, *supra* note 19. With regard to overbuying in general, see Kirkwood, *supra* note 16.; Salop, *supra* note 16.; Richard O. Zerbe, Jr., *Monopsony and The Ross-Simmons Case: A Comment on Salop and Kirkwood*, 72 ANTITRUST LAW JOURNAL 717 (2005).
[38] The cost for collecting and analyzing big data might be factored in. Currently these costs are being reduced at a rapidly.
[39] Anchustegui and Nowag, *supra* note 5 at 4.
[40] With regard to the identification of vulnerable utilities consumers, see UK DEPARTMENT FOR BUSINESS, ENERGY & INDUSTRIAL STRATEGY, *Consumer Green Paper: Modernising Consumer Markets* (2018), https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/699937/modernising-consumer-markets-green-paper.pdf.
[41] There might also be questions as to whether the competitor would have sufficient access to data to counter in an equally efficient manner.

only premised on the ability to segment customers into marginal and inframarginal ones, which should require considerably lower technical capability than truly individualized pricing.

3. III. ALGORITHMIC TARGETING AND PREDATORY PRICING

Algorithmic targeting has 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 dramatically lowers the costs of predatory and exclusionary conduct and fundamentally alters the cost-benefit analysis for the dominant firm. Algorithmic targeting thus requires 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 is 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.[42] Whether recoupment should be required for a predatory pricing claim has been the subject of a long running debate.[43] Without trying to settle the merit of this debate, this article argues that the possibility of algorithmic targeting renders recoupment so much easier and more feasible, thereby significantly reducing the importance of the recoupment requirement.

A. Recoupment: the Existing Debate

A predator is deemed to have recouped its predation loss if the additional profit earned as a result of successful predation during the recoupment period outweighs the loss it sustains from the below-cost prices during the predation period.[44] The most intuitive way to ascertain recoupment is hence to compare the magnitude of predation losses and post-predation gains.[45] Scott Hemphill calls this "conduct-based" approach, which seeks to estimate directly the expected losses and gains from predation and compare their relative size.[46] 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.[47] 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.[48] In the following discussion we explore the direct and indirect approach and investigate how algorithmic targeting affects their application.

1. *The Direct Approach*

Hemphill describes the direct approach as one under which "a court calculate[s] the incumbent's losses from predation, and calculate[s] (likely) gains after predation has ended, and compare the two to see which is larger."[49] This comparison is not as straightforward as Hemphill seems to suggest. The precise meaning of predation losses is in fact open to interpretation.

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.[50]

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[42] Brooke Group Ltd. v. Brown & Williamson Tobacco Corp., 509 U.S. 209 (1993).
[43] Christopher R. Leslie, *Predatory Pricing and Recoupment*, 113 COLUMBIA LAW REVIEW 1695 (2013). Louis Kaplow, *Recoupment and Predatory Pricing Analysis*, 10 JOURNAL OF LEGAL ANALYSIS 1 (2018). C. Scott Hemphill, *The Role of Recoupment in Predatory Pricing Analyses*, 53 STANFORD LAW REVIEW 1581 (2001).
[44] Leslie, *supra* note 48 at 1699.
[45] Kaplow, *supra* note 48 at 9.
[46] Hemphill, *supra* note 48 at 1590.
[47] *Id.* at 1582–83.
[48] *Id.* at 1587.
[49] *Id.* at 1590.
[50] Steven C. Salop, *Exclusionary Conduct, Effect on Consumers, and the Flawed Profit-Sacrifice Standard*, 73 ANTITRUST LAW JOURNAL 311, 326 (2006).

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*.[51]

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.[52] Application of this standard requires a benchmark against which the loss or sacrifice of profit during the predation period is measured.[53] Salop cautions that the benchmark for comparison under this standard should not be the pre-entry monopolist price.[54] 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). After entry into the monopolized market, the now-former monopolist generally would have an incentive to reduce its price to compete, even if it were not attempting to start a war of attrition to cause the entrant to exit from the market."[55]

Louis Kaplow calls this competitive state "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.[56] 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.[57] The predation loss is then compared with the post-predation gains, which are in turn calculated by comparing the defendant's post-predation monopolist profit with his profit under accommodation.[58]

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.[59] It should be clear that 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. Under the profit sacrifice standard, profit that the defendant would have made in a state of accommodation will also be included.[60] The resultant larger profit sacrifice should make it, all else equal, more difficult for the plaintiff to demonstrate successful recoupment.[61] While generally true, this conclusion also depends 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.[62] 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 his profit and loss if predation never happened.[63] The difficulty with the hypothetical profit standards is that it requires an estimation of the predator's profit in the but-for world, which

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[51] *Id.* at 326. Hemphill, *supra* note 48 at 1590.
[52] Salop, *supra* note 55 at 326–28.
[53] Kaplow, *supra* note 48 at 9.
[54] Salop, *supra* note 55 at 327.
[55] *Id.* at 327.
[56] Kaplow, *supra* note 48 at 9.
[57] *Id.* at 9.
[58] *Id.* at 9.
[59] Salop, *supra* note 55 at 326.
[60] *Id.* at 327–28.
[61] *But see* Kaplow, *supra* note 52 at 9.
[62] *Id.* at 324.
[63] Hemphill, *supra* note 48 at 1597.

is far from easy.[64] 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 easy to administer if recoupment has already taken place as the actual profit and loss for the predator can be ascertained. Application of the standards would be trickier if recoupment has not occurred as estimation of post-predation gains would require guesswork on the part of the courts.[65]

Theoretical soundness needs to be balanced against practicality in choosing between these two sets of standard. 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 be sound. This would be true unless there were systemic biases in the fluctuation of accommodation profits pre- and post-predation, given that the main way in which these two sets of standards differ 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 standard do not produce dramatically different results, the choice between them may come down to administrability. As mentioned earlier, Kaplow espouses the hypothetical profit standards.[66] Hemphill, however, rightly argues that it is very difficult to estimate the likely profits in the counterfactual scenario where predation did not occur.[67] 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.

2. The Indirect Approach

The direct approach seeks to estimate directly and compare the expected losses and gains from predation. An alternative structural[68], or the indirect, approach seems to be the more commonly applied by the U.S. courts.[69] 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.[70]

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.[71] 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.[72] 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.[73] 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 recoupment. It makes no attempt to measure the size of the predation loss and the post-predation gain.[74] 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 complete. 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 competition law.

[64] *Id.* at 1597.
[65] *Id.* at 1597.
[66] Kaplow, *supra* note 48 at 11–12.
[67] Hemphill, *supra* note 48 at 1597.
[68] *Id.* at 1599.
[69] Brooke Group, 509 U.S. at 227.
[70] Hemphill, *supra* note 48 at 1587.
[71] Leslie, *supra* note 48 at 1714.
[72] Hemphill, *supra* note 48 at 1587.
[73] *Id.* at 1587.
[74] Frank H. Easterbrook, *Predatory Strategies and Counterstrategies*, 48 THE UNIVERSITY OF CHICAGO LAW REVIEW 263, 269–70 (1981).

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.[75] The 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.[76]

3. *Algorithmic Targeting and Recoupment*

Having surveyed the traditional standards for ascertaining the likelihood of recoupment, this section turns to explore the 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.

a) *General Impact*

The possibility of algorithmic targeting changes the practice and analysis of predatory pricing in fundamental ways. In a market in which 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.[77] In that case, the determination of the 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 these losses sustained during the entire predation period.

Algorithmic targeting allows the dominant firm to respond to competitive threats in a selective manner. Algorithms allow the dominant firm to differentiate between marginal customers and inframarginal customers.[78] The former are more likely to be enticed by the new entrant's product or lower prices.[79] These customers are the ones whose patronage the dominant firm will need to defend. The ability to distinguish between marginal and inframarginal customers and to offer different prices to them means that the dominant firm can make much more targeted responses in reaction to competitive threats. Instead of cutting prices across the board, it only needs to do so for the marginal customers.[80] It can maintain its previous profit-maximizing price for the inframarginal ones.[81] This allows the firm to minimize the loss it must sustain from below-cost price cutting. Algorithmic targeting allows the dominant firm to practice personalized predatory pricing while keeping the attendant loss to a minimum.

Algorithmic targeting does not only affect predation but also recoupment. While a price increase across the board remains a possibility, it is no longer a necessity with algorithmic targeting. The firm can focus the price increase on the inframarginal customers who are willing to stomach higher prices and will not be easily enticed by a competitor's lower prices to defect.[82] 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 reduces 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.[83] Thus algorithmic targeting allows 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.

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[75] Hemphill, *supra* note 48 at 1597.
[76] *Id.* at 1593.
[77] Einer Elhauge, *Why Above-Cost Price Cuts To Drive Out Entrants Are Not Predatory-and the Implications for Defining Costs and Market Power*, 112 YALE LAW JOURNAL 681, 729–30 (2003).
[78] COMPETITION & MARKETS AUTHORITY, *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 (last visited May 19, 2021).
[79] *Id.* at 9.
[80] *Id.* at 9.
[81] *Id.* at 9.
[82] *Id.* at 9.
[83] ORGANIZATION FOR ECONOMIC COOPERATION AND DEVELOPMENT, *Predatory Pricing* 7 (1989), https://www.oecd.org/competition/abuse/2375661.pdf (last visited May 19, 2021).

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 personalized pricing 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.[84] Existing inframarginal 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 personalized price increases. Therefore, the possibility of algorithmic targeting should improve a dominant firm's ability to recoup its predation losses.

Overall, algorithmic targeting allows 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 needs to be recouped will be smaller and the ease of recoupment will be higher. The probability of successful recoupment is much improved and predatory pricing may no longer be as implausible as the U.S. Supreme Court argued in *Matsushita*[85] and *Brooke Group*. The important question is how the possibility of algorithmic targeting affects the analysis of recoupment under either the direct or the indirect approach.

b) *Impact on the Indirect Approach*

The answer is probably 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.[86] If, in contrast, the loss is assumed 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 is also correspondingly smaller. This means that successful recoupment may no longer require highly favorable market conditions. The structural analysis under the indirect approach may be satisfied under a lower threshold. The plaintiff is no longer required to demonstrate very high or even insurmountable entry barriers or severe constraints on capacity expansion post-predation.

It may even 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 no longer fully encapsulate a dominant firm's ability to impose monopolistic prices to recoup losses.[87] 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 will it be forced to raise prices across the board to recoup losses. This will inevitably result in the defection of some marginal customers.[88] The capacity to implement algorithmic targeting affects 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. While it used to be said that the ability to price discriminate is premised on market power,[89] that may

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[84] Patrick Bolton, Joseph F. Brodley & Michael H. Riordan, *Predatory Pricing: Strategic Theory and Legal Policy*, 88 GEORGETOWN LAW JOURNAL 2239, 2242 (2000).
[85] Matsushita Electric Industrial Co. v. Zenith Radio Corp., 475 U.S. 574.
[86] Hemphill, *supra* note 48 at 1592–93.
[87] Leslie, *supra* note 48 at 1714–17.
[88] ROGER J. VAN DEN BERGH & PETER D. CAMESASCA, EUROPEAN COMPETITION LAW AND ECONOMICS: A COMPARATIVE PERSPECTIVE 93 (1st ed. 2001).
[89] LAWRENCE A. SULLIVAN, WARREN S. GRIMES & CHRISTOPHER L. SAGERS, THE LAW OF ANTITRUST: AN INTEGRATED HANDBOOK 61 (3rd ed. 2016).

no longer be true with the emergence of algorithmic targeting.[90] 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 will allow the new entrant to offer different prices to the dominant firm's existing customers to entice them to defect.[91] For the dominant firm's marginal customers, the entrant can offer competitive but not necessarily the lowest prices. For the inframarginal customers, the entrant may need to offer 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 significant undermine the dominant firm's recoupment. A structural analysis under the indirect approach would be incomplete without regard to other firms' ability to implement algorithmic targeting as well.

c) 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 by a numerical example. Assume the market output level is 100 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 (and an average is used here because of algorithmic targeting) prior to the launch of predation is $100. Further assume that one customer buys one unit of the product, 70 of whom are inframarginal and 30 of whom 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.

1) Actual profit standards

Under the actual profit standards, it is clear that the dominant firm will not suffer a loss after engaging in algorithmic predation. Assuming no fixed costs for the moment, it will make a profit of $3,500 from the inframarginal customers while incurring a loss of $900 from the marginal customers. It still makes 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 will 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.

2) 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 80 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 has thus sacrificed profit by engaging in predation and would therefore have lost profit which 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 remains significant even in the presence of algorithmic targeting.

3) Options for adjustments

The choice of profit standards actually matters in the world of algorithmic targeting and the choice can no longer be made simply based on administrative convenience. It would seem that if competition law is to continue to take predatory pricing seriously, some adjustments would need to be made to the application of

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[90] Oren Bar-Gill, *Algorithmic Price Discrimination When Demand Is a Function of Both Preferences and (Mis)perceptions*, 88 THE UNIVERSITY OF CHICAGO LAW REVIEW 217, 225–27 (2019).
[91] *Id.* at 225–26.

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. One may argue that the continual application of the actual profit standards would effectively eliminate predatory pricing as a competition law violation. Detractors may retort that this overstates the 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 will 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, 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.[92] 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 competition law enforcers. Given that, as Hemphill noted, the hypothetical profit standards is 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 is to apply a narrower market definition. The sub-markets for marginal customers and inframarginal customers could be distinguished.[93] 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.[94] If below-cost price cuts are only applied to the marginal customers, the relevant sub-market will be defined to include only them such that the predation loss will not be diluted by the profits from the inframarginal customers.[95] Such market definition is in some ways 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 the inframarginal ones during the recoupment period. Below-cost price cuts will 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. It is the marginal customers who are most likely to be lured by competing products and thus offered price cuts.[96] Meanwhile, it is the inframarginal customers who are most susceptible to price increases during the recoupment period as they have the lowest price elasticity of demand.[97] The beneficiaries of the price cut are unlikely to be the same as the victims of the price increase. 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 which 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-

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[92] ARTHUR A. THOMPSON, ECONOMICS OF THE FIRM: THEORY AND PRACTICE 126 (5d ed. 1989).
[93] Federal Trade Commission v. Whole Foods Market, Inc., 548 F.3d 1028 (D.C. Cir. 2008).
[94] U.S. Dept. of Justice & Federal Trade Commission, *Horizontal Merger Guidelines (Aug. 2010)* s 4.1.4, http://www.justice.gov/atr/public/guidelines/hmg-2010.html (last visited May 19, 2021).
[95] Whole Foods, 548 F.3d at 1039.
[96] *Id*.
[97] William S. Comanor, *Vertical Price-Fixing, Vertical Market Restrictions, and the New Antitrust Policy*, 98 HARVARD LAW REVIEW 983, 991 (1985).

predation gains thus calculated. This essentially replicates the situation where the below-cost price cut and post-predation price increase were applied to the entire market. It helps to prevent the dilution of the effects of predation by excluding those customers who have been unaffected by it.

While 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 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.[98] 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.[99] Even if recoupment fails and the overall consumer gain outweigh its loss, some customers may still be harmed. In Leslie's case, he argues that the composition of customers may change over time.[100] 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.[101] Otherwise, predatory pricing is actually a boon to customers. The second one is that predatory pricing is only rational on the part of the predator if it is profitable overall, and profitability requires successful recoupment.[102] While we usually do not require a proof of the economic rationality of monopolistic or abusive conduct[103], 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 competition law welcomes if not encourages.[104] 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.[105] 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 degree of correspondence between successful recoupment and exclusionary predatory pricing.[106]

First justification

The first justification has already been addressed. The aggregation of predation loss and gain is only a valid determination of consumer harm if the victims of the loss are 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, probability of recoupment is 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 that, second, consumers overall suffer net harm.[107] If successful recoupment is understood in the first sense, the proof of failed recoupment would be very straightforward. All that is required is a showing that some victims of post-

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98 Leslie, *supra* note 48 at 1742.
99 *Id.* at 1742.
100 *Id.* at 1742.
101 *Id.* at 1709.
102 *Id.* at 1720.
103 But see A. Douglas Melamed, *Exclusive Dealing Agreements and Other Exclusionary Conduct--Are There Unifying Principles?*, 73 ANTITRUST LAW JOURNAL 375 (2006). Gregory J. Werden, *Identifying Exclusionary Conduct Under Section 2: The "No Economic Sense" Test*, 73 ANTITRUST LAW JOURNAL 413 (2006).
104 Barry Wright Corp. v. ITT Grinnell Corp., 724 F.2d 227, 234 (1st Cir. 1983).
105 Leslie, *supra* note 48 at 1710.
106 Kaplow, *supra* note 48 at 9–15.
107 This would be based on a Kaldor-Hicks notion of efficiency. See RICHARD O. ZERBE, ECONOMIC EFFICIENCY IN LAW AND ECONOMICS 4–5 (1st ed. 2001).

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 will 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 likely. Moreover, from a more theoretical perspective, 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.[108] 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 a showing is 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 "the 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."[109] 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.[110] However, documentary intent evidence is unreliable because corporate documents are full of aggressive statements that could be interpreted as evidence of predatory intent when they are nothing more than puffery or corporate bravado.[111] Therefore, we must further resort to evidence of objective intent, which hinges on the profitability of the conduct.[112] 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.[113] The lynchpin for predation is the elimination of rivals in order to take over the market.[114] 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 has significantly minimized 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. The case for requiring a proof of successful recoupment can be more persuasively made. But when the predation loss is much smaller and predation much more easily reversible (individualized discounts probably can be withdrawn without many customers noticing it), firms may be more tempted to give it a try even though they are less confident of successful recoupment. The link between successful recoupment and predatory intent is hence much more tenuous than before.

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. Either the algorithm is only responsible for identifying marginal customers or it also makes the pricing decision.[115] In the former case, "the actual execution of pricing is entirely done by human judgment."[116] In the latter case where prices are set

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[108] Pol Antràs, Alonso de Gortari & Oleg Itskhoki, *Globalization, inequality and welfare*, 108 JOURNAL OF INTERNATIONAL ECONOMICS 387, 388 (2017).
[109] Salop, *supra* note 55 at 320.
[110] Steven R. Beck, *Intent as an Element of Predatory Pricing Under Section 2 of the Sherman Act*, 76 CORNELL LAW REVIEW 1242 (1991).
[111] Ronald A. Cass & Keith N. Hylton, *Antitrust Intent*, 74 SOUTHERN CALIFORNIA LAW REVIEW 657, 675–76 (2001).
[112] Leslie, *supra* note 48 at 1754–56.
[113] Easterbrook, *supra* note 79 at 280–81.
[114] Paul L. Joskow & Alvin K. Klevorick, *A Framework for Analyzing Predatory Pricing Policy*, 89 YALE LAW JOURNAL 213, 259 (1979).
[115] Cassey Lee, *The Landscape of Pricing and Algorithmic Pricing* 21 (2020), https://www.researchgate.net/publication/343575442_The_Landscape_of_Pricing_and_Algorithmic_Pricing (last visited May 19, 2021).
[116] *Id.* at 21.

dynamically by algorithms, the process can be understood as "embedded optimization where real-time pricing decisions are automated".[117] When the pricing decisions are ultimately made by human, the analysis of intent is no different from when algorithms are absent.[118] When pricing decisions are made by an 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."[119] The latter goes beyond adaptive algorithms where with the assistance of machine learning "the software learns how to solve the task from experience."[120] Adaptive algorithms perform two functions, estimation and optimization. The algorithm "estimates market demand using past volumes and prices, and possibly other control variables"[121] and then "chooses the optimal price given the demand estimate and observed past behavior of rivals."[122] 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."[123]

What an adaptive algorithm does depends on what it is programmed to do as the set of rules given to it essentially dictates its operation.[124] 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 algorithm offers individualized prices to customers, it does so because it maximizes short-term profit.[125] If a learning algorithm that is programmed to be profit-maximizing nonetheless engages in below-cost price cutting, it must be because it believes predatory pricing maximizes profit.[126] 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 due to attracting additional customers, charging higher prices to loyal customers, or tacit coordination."[127] 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 which may benefit it across multiple markets.[128] 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.[129] Actual recoupment fails despite the 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.

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[117] *Id.* at 21.
[118] Beck, *supra* note 115.
[119] Emilio Calvano et al., *Algorithmic Pricing What Implications for Competition Policy?*, 55 REVIEW OF INDUSTRIAL ORGANIZATION 155, 158 (2019).
[120] *Id.* at 160.
[121] *Id.* at 158.
[122] *Id.* at 158.
[123] *Id.* at 160.
[124] *Id.* at 158–61.
[125] COMPETITION & MARKETS AUTHORITY, *Pricing algorithms: Economic working paper on the use of algorithms to facilitate collusion and personalised pricing* s 2.10 (2018), https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/746353/Algorithms_econ_report.pdf (last visited May 19, 2021).
[126] Calvano et al., *supra* note 124 at 161–65.
[127] COMPETITION & MARKETS AUTHORITY, *supra* note 130 at s 2.10.
[128] Kaplow, *supra* note 48 at 56.
[129] *Id.* at 57.

This could be due to miscalculation or to unforeseen circumstances. In either case, successful recoupment was expected, which means the algorithm expected the predation scheme to be profitable, which in turn is meant to indicate a predatory intent. This is not the inference that is supposed to be drawn from failed recoupment.[130]

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.

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.[131] 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.[132] 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 role to play in establishing 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[133], eventually a plaintiff must show that the dominant firm charged a price below some appropriate measure of costs.[134] 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 determined that economic irrationality must be shown in a predatory pricing claim, the element of below-cost pricing already serves the purpose.

Critics may argue that below-cost pricing only shows irrationality of the conduct at one moment in time while the recoupment requirement demonstrates the profitability and hence rationality of the predation scheme overall.[135] 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[136], 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.[137] 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

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[130] *Id.* at 4, 60.
[131] Timo Klein, *Autonomous Algorithmic Collusion: Q-Learning Under Sequential Pricing*, *in* TINBERGEN INSTITUTE DISCUSSION PAPER, 30–31 (2020), https://papers.tinbergen.nl/18056.pdf.
[132] COMPETITION & MARKETS AUTHORITY, *supra* note 130 at s 9.1.
[133] Kaplow, *supra* note 48 at 19.
[134] Philip Areeda & Donald F. Turner, *Predatory Pricing and Related Practices under Section 2 of the Sherman Act*, 88 HARVARD LAW REVIEW 697, 712 (1975). We explore cost measurements further down, in section III.C.
[135] Kaplow, *supra* note 48 at 2.
[136] Areeda and Turner, *supra* note 139 at 722–24.
[137] Leslie, *supra* note 48 at 1710–12.

screen.[138] Recall that it was argued earlier that the actual profit standards are no longer a useful benchmark in light of algorithmic targeting. 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.

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 be segregated as distinct components or designated as a threshold inquiry.[139] The probability of recoupment on its own does not tell us whether a price cutting scheme is exclusionary or predatory.[140] 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 now renders recoupment more likely, the requirement seems to have lost much of its informational value. There are scant reasons for maintaining a requirement that gives us little useful information but is difficult to establish. The emergence of algorithmic targeting thus adds further ammunition to Leslie's call for the abolition of the requirement.[141]

The recoupment requirement has been used as a filter in predatory pricing cases in the US.[142] The foregoing discussion casts further doubt on whether the criterion can sensibly be applied in the world of algorithmic targeting. Abolishing the recoupment requirement would shift the focus to price-cost comparison. This would bring US law in line with EU competition law under which proof of recoupment is not needed.[143] Yet, a price-cost comparison in the world of algorithmic targeting is not without its own problems as the next section explores.

4. *Algorithmic Targeting and the Appropriate Price for Price-Cost Comparison*

The possibility of algorithmic personalized targeting also has implications for the price-cost comparison in a predatory pricing claim. In a standard predatory pricing claim, there is a comparison between the prevailing market price and some cost measure. 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[144], average variable cost[145], average avoidable cost[146] and average incremental cost[147] 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 which can be used for the comparison.

In the usual predatory pricing case, the market price will be compared with some measure of cost to determine whether the dominant firm is charging a below-cost price.[148] There can be no viable predatory pricing claim without a below-cost price. With one uniform market price, the price side of the price-cost comparison is relatively straightforward. Identifying a prevailing price is no longer a straightforward endeavor when the dominant firm engages in algorithmic targeting. Multiple prices prevail in the market as customers are offered different prices.

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[138] Kaplow, *supra* note 48 at 15.
[139] Louis Kaplow, *Recoupment, Market Power, and Predatory Pricing*, 82 ANTITRUST LAW JOURNAL 167 (2018).
[140] Leslie, *supra* note 48 at 1741–44.
[141] *Id.* at 1765.
[142] *Id.* at 1710.
[143] Case C-202/07 P France Telecom v Commission ECLI:EU:C:2009:214 para 110-113.
[144] Areeda and Turner, *supra* note 139 at 709–13.
[145] *Id.* at 716–18.
[146] William J. Baumol, *Predation and the Logic of the Average Variable Cost Test*, 39 THE JOURNAL OF LAW AND ECONOMICS 49, 60–62 (1996).
[147] Aaron S. Edlin, *Predatory Pricing: Limiting Brooke Group to Monopolies and Sound Implementation of Price-Cost Comparisons*, THE YALE LAW JOURNAL FORUM 996, 1008–11 (2018).
[148] Areeda and Turner, *supra* note 139.

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.[149] This, however, would run into the same problem that arose in the context of recoupment 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 Guidance Paper) suggests focusing on the price paid for the "'contestable' portion of demand."[150]

The exclusion of the inframarginal customers requires identification of marginal and inframarginal customers. Where the algorithm lacks sophistication it may not offer individual prices but stay within the realm of two-tiered pricing: one standard price and one price to all the marginal customers who are susceptible to the competitive threat.[151] 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 need only 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.

Even where the algorithm is more sophisticated and offers individualized prices, it may be possible to identify the reference price. To the extent that it is possible to discern the classification of customers from the dominant firm's internal system or algorithm[152], the task of calculating an average would be relatively straightforward.[153] 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 not 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.

5. *Algorithmic Targeting and the Appropriate Cost Measure*

a) *The Appropriate Cost Measure: the Existing Debate*

Much more scholarly attention has been paid to the issue of cost in the price-cost comparison.[154] 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) an inclusive measure of average incremental cost that includes revenue reductions on pre-existing (inframarginal) units of output."[155] Each of these cost measures have 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 will need adjustments to be fit for purpose.

b) *Marginal cost*

Philip Areeda and Donald Turner originally propose marginal cost[156] ("MC") as the relevant cost measure in their seminal article on predatory pricing.[157] They note that MC is the relevant cost measure

[149] RICHARD G. LIPSEY & CHRISTOPHER RAGAN, ECONOMICS 210 (2003).
[150] European Commission, Guidance on its enforcement priorities in applying Article 82 of the EC Treaty to abusive exclusionary conduct by dominant undertakings (hereinafter European Commission Guidance Paper) [2009] OJ C 45/7 para 39, see in particular para 41.
[151] Calvano et al., *supra* note 124 at 158.
[152] COMPETITION & MARKETS AUTHORITY, *supra* note 130 at s 9.1.
[153] Klein, *supra* note 136 at 31.
[154] Areeda and Turner, *supra* note 139. Baumol, *supra* note 151. Edlin, *supra* note 152.
[155] Edlin, *supra* note 152 at 1011–12.
[156] Marginal cost is the cost associated with the production of one additional unit.
[157] Areeda and Turner, *supra* note 139 at 701–02.

because "in deciding whether it would increase or decrease output, the firm looks to the *incremental* effects on revenue and costs."[158] (italics in original) 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.[159]

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."[160] The essence of his argument is that pricing above MC does not rule out the possibility of profit sacrifice.[161] 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 reduces prices offered to the inframarginal customers such that overall profitability is reduced.[162] The firm may still sacrifice profits even though the price is above MC.[163] 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 yet 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 characterizes the marginal cost test as "not altogether convincing"[164] and "not get[ting] at the issue"[165]. Echoing Edlin's view, Baumol asserts that "there 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."[166]

c) 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 with which accountants are familiar and which accountants calculate.[167] They proceed to propose average variable cost[168] ("AVC") as a proxy for MC and various modifications to a dual-cost rule involving both marginal cost and average variable cost.[169] Einer Elhauge summarizes the convoluted rule that is ultimately proposed by Areeda and Turner as follows: "in 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."[170]

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."[171] 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 competitor. William Baumol and Herbert Hovenkamp have expressed similar views.[172] The AVC test has also been defended on the grounds of administrability as AVC is

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[158] *Id.* at 701–02.
[159] *Id.* at 712.
[160] Edlin, *supra* note 152 at 1006.
[161] *Id.* at 1006–07.
[162] *Id.* at 1007.
[163] *Id.* at 1007.
[164] Baumol, *supra* note 151 at 54.
[165] *Id.* at 55.
[166] *Id.* at 55.
[167] Areeda and Turner, *supra* note 139 at 716.
[168] Average variable cost equals the total variable costs divided by the number of units sold.
[169] Areeda and Turner, *supra* note 139 at 717–18.
[170] Elhauge, *supra* note 82 at 705.
[171] Joskow and Klevorick, *supra* note 119 at 251.
[172] Baumol, *supra* note 151 at 56. Herbert Hovenkamp, *The Law of Exclusionary Pricing*, 4 (2006), http://ssrn.com/abstract= 876968 (last visited May 19, 2021).

much easier to calculate than MC.[173] The test is used by the European Court of Justice to establish a presumption of predation.[174]

The AVC has not been immune from criticism, however. Similar to the MC test, Edlin condemns the one-sided nature of the AVC test.[175] Hovenkamp notes that AVC is not without its own difficulties in calculation. The line between fixed and variable costs are not always clear and joint costs in a multi-product firm can be very tricky to allocate across the various product lines.[176] 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."[177] 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.[178]

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.[179] 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.[180] 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.[181] 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 dominant firm a more lenient standard by which its pricing is judged.

d) 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".[182] 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." In particular, long run AIC includes all product research, development, 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.[183] 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.[184]

A related and very similar concept is the average avoidable costs ("AAC"), which was proposed by William Baumol[185] and features also in the European Commission's Guidance Paper as "the appropriate starting point".[186] 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. Thus, if the period of alleged predation is 10 months, AAC is the sum of the costs incurred in producing the predatory increment over the 10 month period divided by the quantity produced."[187] In particular, AAC "exclude inescapable sunk costs 'that cannot be avoided for some

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[173] Hovenkamp, *supra* note 177 at 4.
[174] Case 62/86 *AKZO Chemie v Commission* EU:C:1991:286, para 71.
[175] Edlin, *supra* note 152 at 1007.
[176] Hovenkamp, *supra* note 177 at 4.
[177] Elhauge, *supra* note 82 at 708.
[178] Hovenkamp, *supra* note 177 at 5–6.
[179] Joseph F. Brodley & George A. Hay, *Predatory Pricing: Competing Economic Theories and the Evolution of Legal Standards*, 66 CORNELL LAW REVIEW 738, 754 (1981).
[180] Elhauge, *supra* note 82 at 711.
[181] *Id.* at 716–17.
[182] Edlin, *supra* note 152 at 1008.
[183] Bolton, Brodley, and Riordan, *supra* note 89 at 2272.
[184] European Commission Guidance Paper, *supra* note 150, at paras. 43-44, 60, 80.
[185] Baumol, *supra* note 151.
[186] European Commission Guidance Paper, *supra* note 150, at para. 64.
[187] Bolton, Brodley, and Riordan, *supra* note 89 at 2271–72.

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.'"[188] (internal quotations original)

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.[189] AAC is a short-run concept because over the long run, all costs, including previously inescapable sunk costs, should be avoidable.[190] 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.[191]

According to Elhauge, this effectively turns the predatory pricing claim into a profit maximization obligation, which he rejects.[192] 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."[193] In contrast, Edlin insists that the incremental revenue-cost comparison is in fact the "ideal" test because it directly measures sacrifice.[194] Edlin therefore advocates an inclusive measure of costs that includes foregone profits whereas Elhauge supports the 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.

1) 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. This question may have salience in the pre-digital age, it has little relevance when algorithmic targeting is possible. The dominant firm is no longer 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.

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.[195] 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.[196] 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. 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."[197] 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."[198] In other words, Elhauge seems to embrace the AIC test with the caveat of the exclusion of foregone profits.

While there are minor disagreements as to whether some inescapable sunk costs should be included, the consensus seems to be that the appropriate cost measure should encapsulate the additional costs

[188] Elhauge, *supra* note 82 at 705–06.
[189] Baumol, *supra* note 151 at 58. European Commission Guidance Paper, *supra* note 150, at para. 26.
[190] Bolton, Brodley, and Riordan, *supra* note 89 at 2271–72.
[191] Elhauge, *supra* note 82 at 694.
[192] *Id.* at 694.
[193] *Id.* at 694–95.
[194] Edlin, *supra* note 152 at 1010–11.
[195] Areeda and Turner, *supra* note 139 at 703–04.
[196] Elhauge, *supra* note 82 at 711.
[197] *Id.* at 712.
[198] *Id.* at 724–25.

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',[199] or the marginal customer or sales. The appropriate cost measure is the cost incurred in supplying the marginal customers to whom below-cost prices are offered. The difficulty here, as before, is that prices will not be uniform with algorithmic targeting. Instead, the dominant firm will offer individualized price cuts to the extent necessary to respond to the competitive threat.

While each customer might receive an individualized price, it may still be possible to identify two groups of potential customers for the entrant, those who are currently the dominant firm's customers and those who are not.[200] 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 from 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.

Thus, to respond to the 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[201], 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 to 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 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.[202] The line between fixed and variable costs could already be murky

[199] European Commission Guidance Paper, *supra* note 150, at para. 41.
[200] 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.
[201] Elhauge, *supra* note 82 at 782.
[202] *Id.* at 724–25.

in traditional situations.[203] These costs may become even more difficult to distinguish under algorithmic targeting, 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 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, has been shut down, or the company stops the use of the algorithm in light of allegations of predation.

Second, algorithmic targeting raises 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 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. 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.

4. VI. ALGORITHMIC TARGETING AND REBATES

Algorithmic targeting can also be used in the context of rebates and creates similar problems. The EU has a relatively more developed jurisprudence on rebates as compared to the US. The EU rules on rebates are at their core about the burden of proof. Rebates are classified into three different types under EU law. On one end of the spectrum are quantitative rebates, which are applied across the board to every increase in sales.[204] These are unproblematic. On the other end of the spectrum are fidelity or loyalty rebates[205], which are (rebuttably) presumed to be abusive.[206] In between these is a third category of rebates. In *Intel*, the General Court held that rebates that are incapable of foreclosing competition are compatible with Article 102.[207] The Court of Justice expanded upon this finding, clarifying that rebates, even fidelity or loyalty rebates, need to be examined in detail in individual cases to establish whether they are capable of foreclosing rivals. The Court, however, stopped sort of requiring actual proof of foreclosure.[208]

The Guidance Paper focuses on whether the rebate is conditional and has a foreclosure-effect.[209] In this assessment the as-efficient competitor test plays a crucial role.[210] In general, the test follows the principles developed for predatory conduct. The Commission identifies the "relevant range"[211] and examines whether the prices are above the Long Run Average Incremental Costs (LRAIC), below the LRAIC but above the AAC, or below the AAC.[212] When rebates are above the LRAIC foreclosure effects are unlikely, while rebates below the AAC has the capability of foreclosing equally efficient competitors. Between the LRAIC and the AAC, the Commission will look into 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

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[203] Hovenkamp, *supra* note 177 at 4.
[204] ALISON JONES, BRENDA SUFRIN & NIAMH DUNNE, EU COMPETTION LAW: TEXT, CASES, AND MATERIALS 449–50 (7th ed. 2019).
[205] In other words, these are rebates that are conditioned on exclusively buying from the dominant firm.
[206] Case C-85/76, *Hoffmann-La Roche* EU:C:1979:36, para 89-90.
[207] Case T-286/09 *Intel Corp v European Commission* EU:T:2014:547 para 74-78.
[208] Case C-413/14 P *Intel v Commission* ECLI:EU:C:2017:632 para 129-147, see also Case C-23/14, *Post Danmark II* EU:C:2015:651 para 27.
[209] European Commission Guidance Paper, *supra* note 150, at paras. 37-45.
[210] Case C-413/14 P Intel v Commission ECLI:EU:C:2017:632 para 138-147; European Commission Guidance Paper, *supra* note 150, at paras. 39-45.
[211] *Id.* at paras. 43–44.
[212] *Id.* at para. 44.

have such counterstrategies at their disposal, the Commission will consider that the rebate scheme is capable of foreclosing equally efficient competitors.[213]

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 identify the individual marginal customer or the marginal transaction, it will not be able to compete. The dominant firm is 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 for the competitor.[214] A more detailed discussion of the impact of algorithmic targeting on the as-efficient competitor test will 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'"[215] faces the same problems as those that have been 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.

5. V. ALGORITHMIC TARGETING AND TYING AND BUNDLING

Unsurprisingly, algorithmic targeting does not only change the assessment of predation and rebates but also the analysis of tying and bundling. A firm intent on pursuing a tie will 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 the firm seeks to impose 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.[216] This type of customers will accept the tie and purchase the tying firm's bundle.[217] This could because they do not have 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 additional consumer surplus from a rival's tied product over the tying firm's tied product outweighs the additional consumer surplus from the tying firm's tying product over a rival's tying product.[218] These customers will balk at being forced to take the tying firm's tied product.[219] 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 particular by means of a variable-proportions tie.[220] In the long run, the tying firm hopes to

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[213] *Id.* at para. 44.
[214] On the challenges with regard to the as-efficient competitor test see infra Section VI.
[215] EUROPEAN COMMISSION, *supra* note 202 at para. 42.
[216] Meyer L. Burstein, *The Economics of Tie-In Sales*, 42 THE REVIEW OF ECONOMICS AND STATISTICS 68, 69 (1960).
[217] Frank Mathewson & Ralph Winter, *Tying as a response to demand uncertainty*, 28 RAND JOURNAL OF ECONOMICS 566, 573 (1997).
[218] Meyer L. Burstein, *The Economics of Tie–In Sales*, 42 REVIEW OF ECONOMICS AND STATISTICS 68, 69 (1960).
[219] Mathewson and Winter, *supra* note 222 at 573.
[220] Erik Hovenkamp & Herbert J. Hovenkamp, *Tying Arrangements and Antitrust Harm*, 52 ARIZONA LAW REVIEW 925–76, 928–29 (2010).

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.[221]

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.[222] Through such a tie, the tying firm can extract extra consumer surplus from customers who place particularly high valuation on the tying product.[223] At the dynamic level, the benefits of tying consist of the extra profit the tying firm makes 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 arise from 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 firm's tying product.[224] 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 US and the EU only condemn ties implemented by firms with a sufficient degree of market power in the tying product market. In the US, the *Jefferson Parish* case lays down a safe harbor from the qualified per se rule for tying so long as the tying firm has less than a 30% market share in the tying product market.[225] In the EU, tying and bundling are regulated as abuse of dominance, which generally requires a market share of around forty percent.[226] Currently, the European Commission uses a predation-based test for its assessment of the exclusionary effect of such behavior. It uses the incremental price[227] 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.[228] 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.

B. Tying in the World of Algorithmic Targeting

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

1. Lower Market Power Threshold for an Anticompetitive Tie

First and foremost, it greatly alleviates the most fundamental trade-off confronting a tying firm. What ultimately necessitates this trade-off is the fact that a tie cannot be imposed selectively and must be implemented across the board. A tying firm cannot distinguish between inframarginal and marginal customers and must impose the tie upon uniformly.

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[221] Michael D. Whinston, *Tying, Foreclosure, and Exclusion*, 80 THE AMERICAN ECONOMIC REVIEW 837–59 (1990). Barry Nalebuff, *Bundling as an Entry Barrier*, 119 THE QUARTERLY JOURNAL OF ECONOMICS 159–187 (2004). Jay Pil Choi & Christodoulos Stefanadis, *Tying, investment, and the dynamic leverage theory*, 32 RAND JOURNAL OF ECONOMICS 52–71 (2001). Jay Pil Choi, *Preemptive R&D, Rent Dissipation, and the "Leverage Theory"*, 111 QUARTERLY JOURNAL OF ECONOMICS 1153 (1996).
[222] Ward S. Bowman, Jr., *Tying Arrangements and the Leverage Problem*, 67 YALE LAW JOURNAL 19–37, 23–24 (1957).
[223] Nicholas Economides, *Tying, bundling, and loyalty/requirement rebates*, *in* RESEARCH HANDBOOK OF THE ECONOMICS OF ANTITRUST LAW 121, 125 (Einer Elhauge ed., 2012).
[224] HERBERT HOVENKAMP, FEDERAL ANTITRUST POLICY: THE LAW OF COMPETITION AND ITS PRACTICE s 3.1a (4th ed. 2011).
[225] Jefferson Parish Hospital District No. 2 v. Hyde, 466 U.S. 2, 26 (1984).
[226] JONES, SUFRIN, AND DUNNE, *supra* note 209 at 337.
[227] Where possible incremental costs.
[228] European Commission Guidance Paper, *supra* note 150, at para. 60.

Algorithmic targeting resolves this dilemma by allowing the tying firm to differentiate its customers.[229] Once customer differentiation is feasible, 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 now avoids or at least minimizes the loss of profits from customer defection. In fact, profits from the inframarginal customers can be used to subsidized 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 the market power threshold for a potentially anticompetitive tie is now lower. A tie can harm customers at a considerably lower level of market power in the tying product market.

2. *Facilitation of Offensive Leveraging*

Algorithmic targeting also makes 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.[230] Offensive leveraging refers to when a firm which possesses significant market power in the tying product market leverages that power to gain a competitive advantage in the tied product market.[231] Rivals in the tied product market are 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.[232] Algorithmic targeting seems to have a greater role to play in the static models. It generally renders tying a more effective tool for offensive leveraging. This is accomplished in three main ways.

First, it turns tying into a less costly and more profitable strategy for the tying firm. Algorithmic targeting allows 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 do so is key to the success of foreclosure in a number of economic models.[233]

Second, algorithmic targeting allows the tying firm more effectively to deny rivals 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.[234] The tying firm may attempt to hold on to market shares by offering bundled discounts to marginal customers so that customers eschew the entrant's tied product.[235] Tying thus achieves foreclosure by leaving entrants with insufficient scale to make entry viable.[236] A tying firm's ability to capture market share is contingent on its ability to entice customers with bundled discounts.[237] With algorithmic targeting, 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. Personalized discounts allow the firm to hang on to more customers, hence leaving even fewer of them to the new entrant. The new entrant is 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 personalized discounts offered to the marginal customers can be cross-subsidized by the extra profits from the inframarginal customers subject to the tie.

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[229] COMPETITION & MARKETS AUTHORITY, *supra* note 83 at 9.
[230] Bowman, Jr., *supra* note 227 at 30.
[231] Whinston, *supra* note 226.
[232] Michael Whinston's and Barry Nalebuff's are both static models while the two models by Jay Pil Choi are dynamic in nature and are premised on innovation.
[233] Dennis W. Carlton & Michael Waldman, *Robert Bork's Contributions to Antitrust Perspectives on Tying Behavior*, 57 JOURNAL OF LAW & ECONOMICS S121, 216 (2014). Barry Nalebuff, *Bundling as an Entry Barrier*, 119 THE QUARTERLY JOURNAL OF ECONOMICS 159–187, 168 (2004).
[234] Nalebuff, *supra* note 238 at 165.
[235] *Id.* at 169–70.
[236] DENNIS W. CARLTON & MICHAEL WALDMAN, *Theories of Tying and Implications for Antitrust* 14 (2005).
[237] *Id.* at 14.

Third, algorithmic targeting makes 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.[238] 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.[239] The incumbent foregoes profits from sales in the tying product market when pursuing a tie.[240] 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.[241]

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.[242] 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.[243] 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."[244]

With algorithmic targeting, the tying firm can 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 will be spared the tie. The minimization of loss of profits means that tying is a more plausible strategy even absent a credible pre-commitment to tie. A tying firm no longer needs to pursue costly actions such as product redesigns or changes in the production process to signal its intention to tie. Tying hence becomes a more flexible and potent tool for offensive leveraging, which should increase the likelihood that tying is used to achieve foreclosure and augment the anticompetitive potential of tying.

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

Algorithmic targeting significantly weakens price discrimination as a 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.[245] The quintessential example is printers and replacement ink cartridges.[246] The seller of the tying product, however, is unable to distinguish between high-intensity and low-intensity users and vary its prices accordingly.[247] 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.[248] The seller can tie the sale of the tying product to the sale of a tied product at supra-competitive prices.[249] 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.[250] The possibility of price discrimination is thus often used as a procompetitive justification for tying.

Algorithmic targeting renders 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. Algorithms alleviate the first problem by

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[238] Whinston, *supra* note 226 at 840.
[239] *Id.* at 840.
[240] *Id.* at 844.
[241] *Id.* at 844–45.
[242] *Id.* at 840.
[243] *Id.* at 839.
[244] *Id.* at 840.
[245] Bowman, Jr., *supra* note 227 at 23–24.
[246] Einer Elhauge, *Tying, Bundled Discounts, and the Death of the Single Monopoly Profit Theory*, 123 HARVARD LAW REVIEW 397–481, 404 (2009).
[247] Bowman, Jr., *supra* note 227 at 23.
[248] *Id.* at 23–24.
[249] *Id.* at 24.
[250] Hovenkamp and Hovenkamp, *supra* note 225 at 928–29.

helping the firm to different customers and charge them different prices.[251] Direct price discrimination becomes possible with algorithms, obviating the need to resort to a tie. With algorithms, firms should be able to draw finer distinctions than 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.

Algorithms do not rule out price discrimination as a justification for tying entirely; it is not clear whether algorithms also render ties redundant for the purpose of intra-consumer and inter-product price discrimination.[252] 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 allows tying to harm customers at a lower level of market power, renders much less persuasive a commonly invoked justification for tying, and makes 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.

6. 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 US, the as-efficient competitor is an important benchmark in assessing exclusionary conduct.[253] As mentioned earlier, the EU approach to predation as well as rebates, and tying and bundling strongly relies on the as-efficient competitor test.[254] Since the *Intel* judgment some even see it the central theme of the EU's abuse of dominance prohibition protecting only efficient competitors.[255] The importance of the as-efficient competitor test stems from 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.[256] 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.[257] Tests such as the profit sacrifice test or the no-economic sense test are suggested as a remedy. 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.[258]

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 includes also the ability to identify marginal customers and engage in algorithmic targeting. While we might argue that such an ability should be taken into account because the ability to identify and price discriminate will have substantial effects on costs, this leaves some complex questions

[251] COMPETITION & MARKETS AUTHORITY, *supra* note 83 at 9.
[252] George J. Stigler, *United States v. Loew's Inc.: A Note on Block-Booking*, 1963 THE SUPREME COURT REVIEW 152–57 (1963). Burstein, *supra* note 223.
[253] With regard to rebates, see 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 (2018).
[254] EUROPEAN COMMISSION, *supra* note 216 at 138–47.
[255] Pablo Ibáñez Colomo, *The Future of Article 102 TFEU after Intel*, 9 JOURNAL OF EUROPEAN COMPETITION LAW & PRACTICE 293 (2018).
[256] Kai-Uwe Kuhn & Miroslava Marinova, *The Role of the As-Efficient-Competitor After the CJEU judgment in Intel*, 4 COMPETITION LAW AND POLICY DEBATE 67 (2018).
[257] Friso Bostoen, *Online Platforms and Pricing: Adapting abuse of dominance assessments to the economic reality of free products*, 35 COMPUTER LAW AND SECURITY REVIEW 268 (2019).
[258] Kuhn and Marinova, *supra* note 261 at 68.

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 distinguish between marginal and inframarginal customers.

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 off-set by another group of customers. A compounding factor in the case of algorithmic predation and exclusion are the well-known problems that result from the amalgamation of data troves.[259] 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, which 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 on 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 competition 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?[260] Would a competition policy approach that allows/encourages such behavior not ultimately lead to an economy which consists only of monopolized markets?

7. 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. Artificial intelligence will continue to require us to revisit fundamental assumptions about firm and consumer behavior that underpins many antitrust doctrines. As artificial intelligence and other related technology becomes more advanced, the interaction between firms and consumers will continue to evolve. It is imperative that antitrust law 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.

[259] See e.g., JACQUES CREMER, YVES-ALEXANDRE DE MONTJOYE & HEIKE SCHWEITZER, *Competition Policy for the Digital Era: Report of the European Commission* (2019), https://ec.europa.eu/competition/publications/reports/kd0419345enn.pdf.; JASON FURMAN ET AL., *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.; JAPANESE MINISTRY OF ECONOMY, TRADE & INDUSTRY, *Fundamental Principles for Rule Making to Address the Rise of Platform Businesses Formulated* (2018), https://www.meti.go.jp/english/press/2018/1218_002.html.; L'AUTORITÉ DE LA CONCURRENCE & BUNDESKARTELLAMT, *Competition Law and Data: joined report by the German and French Competition Authority*.

[260] For a similar argument regarding significant economies of scale and/or scop, Kuhn and Marinova, *supra* note 261 at 63.