The Implications of Algorithmic Pricing for Coordinated Effects Analysis and Price Discrimination Markets in Antitrust Enforcement

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WHEN CONGRESS ENACTED THE Sherman and Clayton Acts over a century ago, the term "robot" did not exist.[1] The framers of our antitrust laws would likely be amazed by the increasingly powerful and autonomous technologies, such as algorithms, machine learning, and artificial intelligence (AI) that have come to play a significant role in many firms' competitive behavior. These technologies have the potential to deliver meaningful consumer benefits. For example, algorithms may enable firms to become more efficient and to provide consumers with personalized product recommendations. Big data and algorithms may also provide companies with insights that help them design better products and services.

But these technologies are also likely to present novel challenges for competition enforcers. We must understand the potential effects of intelligent, high-velocity pricing technologies on competition and adapt our enforcement approach to keep pace. For example, algorithmic pricing might contribute to overt collusion or facilitate tacit collusion. It is also possible, as we show in this article, that increasingly sophisticated price discrimination may lead to narrower relevant product markets, potentially increasing the chances that a merger will harm consumers in some relevant market.

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Algorithmic Collusion

Some applications of antitrust law in the age of machines will be familiar. For example, the Department of Justice recently prosecuted two e-commerce sellers for agreeing to align their pricing algorithms to increase online prices for posters.[2] In that case, *United States v. Topkins*, the humans reached an explicit agreement to use technology to fix prices. The application of antitrust law to that agreement was straightforward.

As algorithms and the software running them become more sophisticated, however, coordinated behavior may become more common without explicit "instruction" by humans. Challenging conduct where the role of humans in decision making is less clear may be more difficult under current law.[3] For example, while express collusion is illegal, mere conscious parallelism is not.[4] Separating one from the other can prove difficult even when dealing with solely human decision making. Professor Salil Mehra suggests that the rise of "robo-sellers" may make the task more difficult still: a number of current inquiries used to distinguish conscious parallelism from express collusion will be of limited use in the machine context. Concepts such as "intent" and "meeting of the minds," he writes, "presuppose quintessentially human mental states" and thus "may prove less useful in dealing with computer software and hardware."[5]

Algorithms Might Contribute to Overt Collusion. The defendants in *Topkins* used pricing algorithms as an instrument to facilitate a pre-arranged price fixing conspiracy.[6] In their recent book, *Virtual Competition*, Professors Ariel Ezrachi and Maurice Stucke refer to this as a "messenger" scenario: the pricing algorithms were following explicit human instructions to violate the antitrust laws and thus merely acting as "messengers" among the various co-conspirators.[7]

It is worth pausing to consider why the *Topkins* defendants chose to employ algorithms rather than setting prices and monitoring their agreement directly. Algorithms may facilitate the stability of certain price-fixing schemes by enabling firms to more quickly detect, and respond to, attempts to cheat on the collusive pricing agreement. The U.S. antitrust agencies' 2010 Horizontal Merger Guidelines specifically note that speed in identifying and responding to competitors' strategic initiatives is a factor that makes markets more vulnerable to coordinated conduct. Swift competitive reaction times diminish each firm's "prospective competitive reward from attracting customers away from its rivals."[8]

Margrethe Vestager, the European Commissioner for Competition, recently remarked on the potential for algorithms to sustain cartel behavior:

> Every cartel faces the risk that its members will start cheating each other as well as the public. If everyone else's price is high, you can gain a lot of customers by quietly undercutting them. So whether cartels survive depends on how quickly others spot those lower prices, and cut their own price in retaliation. By doing that quickly, cartelists can make sure that others will be less likely to try cutting prices in the

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> future. And the trouble is, automated systems help to do exactly that.[9]

Competition enforcers must recognize the possibility that algorithms might facilitate cartel formation and maintenance. Detection of such arrangements may require novel investigative approaches or additional resources.[10] From a legal perspective, however, the analysis of the messenger scenario is "relatively straightforward."[11] Once detected, competition enforcers have the tools to challenge overt collusion. As Vestager put it, "no one should imagine they can get away with price-fixing by allowing software to make those agreements for them."[12]

Algorithms Might Facilitate Tacit Collusion. A second possibility is that algorithms may facilitate *tacit* collusion between competitors. Ezrachi and Stucke describe this as the "predictable agent" scenario.[13] Professor Salil Mehra notes that "automated pricing powered by algorithmic processing and mass data collection should reduce the costs to firms [of] interdependent pricing."[14]

The analysis closely follows that above, with the focus again on the speed with which algorithms can identify and react to changing market dynamics.[15] Mehra posits that pricing algorithms will surpass humans in their ability to achieve and sustain elevated prices through coordinated interaction: "the increased accuracy in detecting changes in price, greater speed in pricing response, and reduced irrationality in discount rates all should make the robo-seller a more skillful oligopolist than its human counterpart in competitive intelligence and sales."[16] Ezrachi and Stucke contend that "as competitors' prices shift online, their algorithms can assess and adjust prices—even for particular individuals at particular times and for thousands of products—within milliseconds. In other words, they can swiftly match a rival's discount, thus eliminating its incentive to discount in the first place."[17]

Bruno Salcedo goes a step farther in his recent paper, *Pricing Algorithms and Tacit Collusion*. Salcedo finds that under certain conditions, tacit collusion between firms employing pricing algorithms "is not only possible but rather, it is *inevitable*."[18] Salcedo's findings "suggest that pricing algorithms are an effective tool for *tacit* collusion" and may lead to near-monopolistic pricing.[19]

It is probably too soon to assess the generality of the conditions underlying Salcedo's model. For example, Salcedo's model assumes that firms can, and do, decipher their competitors' algorithms.[20] Commentators correctly note that various features of pricing algorithms may increase market price transparency and reduce reaction times among competitors.[21] But other features of pricing algorithms may enable firms to reduce transparency and mask their competitive initiatives. Algorithms can enable companies to engage in sophisticated price discrimination involving a combination of differential "list" prices and targeted discounts. Salcedo's paper models a scenario in which firms have "the option to obfuscate their algorithms so they can never be decoded" but his model finds that, even with this option, firms "would never choose to obfuscate their algorithms."[22]

The increasing power of algorithms and AI may indeed lead to more coordinated interaction but it is too early to say this with certainty. Future research may prove especially valuable in this area. If, in fact, new technologies are found to make coordinated interaction between competitors more likely, that would provide a strong argument for an enhanced focus on coordinated effects in merger analysis and for lower thresholds of concern related to coordinated effects.

Notably, the use of a pricing algorithm, by itself, does not raise antitrust concerns. And as the DOJ's successful prosecution of algorithmic price fixing shows, enforcers will be able to identify and challenge the improper use of these new technologies in many cases. Nonetheless, the potential that pricing algorithms will facilitate tacit collusion beyond the reach of Section 1 of the Sherman Act is far from fanciful. Indeed, the Federal Trade Commission's authority under Section 5 of the FTC Act to prosecute "unfair methods of competition" may be the only current tool available to police individual instances of algorithmic collusion.[23]

Price Discrimination Markets

To price discriminate successfully (i.e., charge different prices to different groups of consumers), firms must possess some degree of market power and there must be factors limiting the potential for buyers' arbitrage. Economists recognize three main types of price discrimination: (1) first-degree, or so-called perfect price discrimination, in which each customer is charged a different price that perfectly matches his or her willingness to pay; (2) second-degree price discrimination, in which price depends on the quantity purchased (e.g., the seven-pound container of ketchup at your local wholesale club); and (3) third-degree price discrimination, in which consumers are sorted based on observable characteristics related to willingness to pay (e.g., student discounts).[24]

First-degree price discrimination is considered the holy grail of price discrimination because it allows the seller to capture all available consumer surplus in a market. Professor John Gourville has observed that "[h]istorically, first-degree price discrimination has been very difficult to implement, mostly for logistical reasons."[25] But that appears to be changing, as companies are gathering ever more data about consumers at an individual level and learning to analyze and use that data in increasingly nuanced ways. A 2014 White House report on big data noted: "[T]he volume of information that people create themselves—the full range of communications from voice calls, emails and texts to uploaded pictures, video, and music—pales in comparison to the amount of digital information created about them each day."[26]

More data and more powerful, faster analytics are enabling companies to sort customers into smaller and smaller groups. In 2014, the FTC issued a report on data brokers. The report found that brokers "hold a vast array of information on individual consumers" and noted that a single data broker "has 3000 data segments for nearly every U.S. consumer."[27] Companies are embracing pricing personalization as a business strategy. In 2013, Safeway's CEO explained 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."[28] As price discrimination strategies become more individualized, they may begin to exhibit characteristics of first-degree price discrimination.[29] Ezrachi and Stucke suggest that "[p]erfect price discrimination may be unattainable. But 'almost perfect' behavioral discrimination may be within reach."[30]

Consumers generally find the practice of price discrimination objectionable.[31] As a matter of economic theory, however, the consumer welfare effects of price discrimination are ambiguous—and targeted price discrimination may actually benefit consumers in some situations.[32] Price discrimination can increase market output and lower prices for certain groups of consumers. Indeed, some products and services would not be offered at all without price discrimination. As with tacit collusion, unilateral price discrimination is not, in and of itself, an antitrust violation. At the same time, as we explain below, algorithm-enabled price discrimination could significantly influence the merger review process in the near future by creating narrower product markets.

Increasingly Nuanced and Profitable Price Discrimination Strategies by Sellers Could Lead to Narrower Product Markets. Initially the Internet enabled more customers to access the same products at the same prices. This feature of digital commerce helped to flatten former geographic variations in pricing. In many cases, the growth of e-commerce contributed to a broadening or "merging" of regional relevant geographic markets.[33] Even if you lived in a region where the brick-and-mortar price for an item was unusually high, to an online retailer you were just another customer in a much broader sales area. From a pricing perspective, you were largely anonymous.

Cartoonist Peter Steiner summarized this principle brilliantly in 1993 in what is now the most reproduced cartoon in *The New Yorker*'s history. In the cartoon, a dog sitting at a computer turns to his canine companion and explains: "On the Internet, nobody knows you're a dog."[34]

Big data and powerful algorithms are turning that principle on its head. Today's dog might well tell his companion: "On the Internet, everybody knows you're a dog." We are hardly the first to make this observation. As far back as 2003, Andrew Odlyzko wrote that "in practice, there are many who not only know you are a dog but are familiar with your age, breed, illnesses, and tastes in dogfood."[35] In fact, today's technology not only knows these intimate details about consumers, it can also make predictions about their behaviors and desires. So even though the rise of digital commerce has historically led to a broadening of markets, increasingly sophisticated pricing algorithms could lead to narrower product markets in the future as a result of price discrimination strategies.

Under the 2010 Horizontal Merger Guidelines, the agencies specifically evaluate the possibility of price discrimination against targeted customers.[36] The Guidelines note that price discrimination "may involve identification of individual customers to which different prices are offered or offering different prices to different types of customers based on observable characteristics."[37] Moreover, the Guidelines explain that "[w]hen discrimination is reasonably likely, the agencies may evaluate competitive effects separately by type of customer."[38] The agencies have taken this approach in radio markets for example.[39] Price discrimination markets also played a significant role in the FTC's successful challenge to the merger of Sysco and U.S. Foods.[40]

The Guidelines do not net out consumer welfare gains in one market against losses in another. If a targeted group of customers will be harmed by a loss of competition, that in and of itself is sufficient grounds to justify blocking the transaction. As Judge Sullivan wrote in *FTC v. Staples*, "Antitrust laws exist to protect competition, even for a targeted group that represents a relatively small part of an overall market."[41] The Guidelines state that "[t]he Agencies normally assess competition in each relevant market affected by a merger independently and normally will challenge the merger if it is likely to be anticompetitive in any relevant market."[42] The agencies may consider the broader effects of a transaction outside a specific relevant market in certain cases, but the Guidelines are clear that the decision to do so is an exercise of prosecutorial discretion.[43] With that in mind, below are three examples that illustrate how big data and algorithms could lead to narrower product markets defined on the basis of price discrimination.

Example 1: Price Discrimination Based on Car Ownership. Consider a product that serves a time-sensitive need of consumers. The product is sold by three online retailers (A, B, and C) and by three brick-and-mortar retailers (D, E, and F). Consumers are able to obtain the product immediately from the brick-and-mortar retailers. To compete, Firms A, B, and C advertise free overnight shipping. Firm A also employs a pricing algorithm that offers different prices to different consumers based on a variety of factors.[44] Firm A proposes to acquire Firm B. The companies point to compelling evidence of intense firm-level competition with brick-and-mortar retailers. Firm A's documents, however, reference data analytics showing that consumers who live in households without a car are considerably more likely to purchase the product online. Assuming the combined firm's pricing algorithm can identify those consumers, the merger could enable the combined firm to increase prices selectively to customers without automobiles.[45] Over 90 percent of U.S. households have access to a vehicle.[46] Even if the majority of consumers would not be negatively affected by the proposed transaction, however, it may nonetheless be appropriate to define a price discrimination market for "product consumers who live in households without a vehicle." As Table 1 shows, the post-merger competitive dynamics facing those consumers would be quite different from those faced by consumers with vehicle access.[47]

Table 1: Price Discrimination Based on Car Ownership

Consumer Category	*Market Structure*	*Remaining Firms*
Car (90%)	6-to-5	A, C, D, E, F
No Car (10%)	3-to-2	A, C

Example 2: Price Discrimination Based on Political Viewpoint. Consider again a market with six firms. Firm C has a reputation for being conservative and publicly supports conservative causes. Firm D has a reputation for being liberal and publicly supports liberal causes. Firms A, B, E, and F are politically neutral. Customer surveys show that most consumers do not take the political affiliations of the companies into account when making their purchase decisions. However, 10 percent of consumers identify as "very liberal" and report being unwilling to buy from Firm C. Another 10 percent identify as "very conservative" and report being unwilling to buy from Firm D. Through big data and analytics, it is possible for firms in the market to determine the political views of prospective customers and to personalize prices on that basis.[48] Firm A proposes to acquire Firm B. As Table 2 shows, the merger would produce a different set of competitive dynamics for each set of consumers.

Table 2: Price Discrimination Based on Political Viewpoint

Consumer Category	*Market Structure*	*Remaining Firms*
Moderate (80%)	6-to-5	A, C, D, E, F
Conservative (10%)	5-to-4	A, C, E, F
Liberal (10%)	5-to-4	A, D, E, F

For the large majority of customers, the merger would reduce the number of sellers from 6 to 5. For those consumers who identify as "very conservative" or "very liberal," however, it would reduce the number of sellers from 5 to 4. Note that liberal and conservative consumers do not face the same 5 to 4. The competitive analysis would thus differ for the two groups. As in the first example, even if the agencies determined that the merger would not be anticompetitive for the majority of consumers, it might still lead to anticompetitive effects for very liberal and/or very conservative consumers. Thus, although it might sound odd from a market definition perspective, the agencies might appropriately define a price discrimination market for "politically liberal product consumers" and/or "politically conservative product consumers."

Examples 1 and 2 involve price discrimination across a single dimension. In the real world, pricing algorithms may engage in price discrimination across multiple dimensions simultaneously. Our third example combines the first two fact patterns to show how multivariate price discrimination can lead to further fracturing of antitrust relevant product markets.

Example 3: Price Discrimination Across Two Dimensions. Consider again a product that serves a time-sensitive need of consumers and is sold by six firms with the following attributes:

Table 3: Firm Attributes

Firm	*Market Presence*	*Political Reputation*
A	Online	Neutral
B	Online	Neutral
C	Online	Conservative
D	Brick & Mortar	Liberal
E	Brick & Mortar	Neutral
F	Brick & Mortar	Neutral

As in Example 1, consumers who live in households without a car are considerably more likely to purchase the product online. And as in Example 2, liberal consumers are unwilling to buy from Firm C and conservative consumers are unwilling to buy from Firm D. Through big data analytics, Firm A is capable of determining both the political views of prospective consumers and whether consumers have access to a vehicle.[49] Firm A proposes to acquire Firm B. Table 4 presents the competitive dynamics facing each set of consumers.

Consumers who live in households with vehicles would face the same competitive dynamics as in Example 2 (depending on their individual political affiliation). Moderate and conservative consumers who live in households without vehicles would face the same competitive dynamics as consumers without vehicles in Example 1. Liberal consumers who live in households without vehicles, however, would now face a merger to monopoly.

It is worth pausing to consider the implications of these examples. First, it may be challenging for antitrust enforcers to detect situations in which algorithmic price discrimination leads to anticompetitive merger effects. At first blush, Example 3 would appear to present a straightforward 6-to-5 merger. And for 72 percent of consumers, it would be just that.[50] Firm-wide diversion numbers in this example would likely obscure the competitive situation faced by specific demographic groups that might be subject to targeted price increases following a merger. Moreover, there would be little reason, ex ante, to suspect that the political views of consumers would be at all relevant in assessing competitive

Table 4: Price Discrimination Across Two Dimensions

Consumer Categories	Car (90%)		No Car (10%)	
Moderate (80%)	6-to-5	A, C, D, E, F	3-to-2	A, C
Conservative (10%)	5-to-4	A, C, E, F	3-to-2	A, C
Liberal (10%)	5-to-4	A, D, E, F	2-to-1	A

effects. Merger enforcement is a fact-specific enterprise, however. Big data and analytics may enable companies to engage in profitable targeted pricing strategies that initially seem arbitrary or even bizarre. (The ability to draw these types of non-obvious connections is, after all, the great promise and peril of big data analytics.) Competition enforcers should therefore be vigilant in reviewing mergers involving sophisticated pricing algorithms and closely examine possibilities for targeted consumer harm.

Second, the size of specific price discrimination markets in which competitive concerns arise may be quite small compared to overall sales for a particular product. In this example, a relevant price discrimination market of "politically liberal product consumers who live in households without a vehicle" would account for just 1 percent of total consumers.[51] Nonetheless, these consumers are highly vulnerable to an anticompetitive post-merger price increase. Indeed, they would likely face monopoly pricing following the merger of Firms A and B.

Third, each additional simultaneous dimension on which price discrimination occurs has the potential to increase the number of relevant markets exponentially. Recall the FTC report cited earlier, which found that a single data broker "has 3000 data segments for nearly every U.S. consumer."[52] The vast majority of these data segments are likely to be competitively insignificant for purposes of pricing any individual good or service. But when considered simultaneously by a pricing algorithm, it only takes a few salient inputs to quickly create a multitude of potential relevant markets.

We are faced, then, with the possibility that sophisticated price discrimination may reverse the trend towards broader relevant product markets in certain cases. A merger that might previously have required an analysis of competitive effects in one relevant product market may instead require antitrust enforcers to examine dozens, if not hundreds, of potential relevant product markets. Both the government and the parties would need to devote more resources to such an investigation. Moreover, the fracturing of relevant product markets on the basis of price discrimination could increase the chances that a given merger will harm consumers in *some* relevant market. In our third example, what might otherwise have been a straightforward 6-to-5 merger became a merger to monopoly for a relevant market made up of liberals without cars.

It may also prove more difficult to fashion appropriate structural remedies for competitive harm in targeted price discrimination markets than for competitive harm in local geographic markets. Often, divesting assets within local geographic markets can address competitive concerns in those markets while permitting the larger transaction to proceed. But companies are less likely to have discrete business assets associated with individual price discrimination markets.

So what are competition enforcers to do? In some cases, enforcers may choose to exercise prosecutorial discretion to permit a merger where the overall benefit to consumers clearly and materially outweighs harm to targeted consumers that cannot be remedied absent blocking the transaction.[53] Alternatively, enforcers may wish to consider making an exception to their general (and well-placed) reticence to accept behavioral remedies, perhaps by accepting agreements by parties to "tether" prices for customers in price discrimination markets of concern to prices in certain other markets.

Conclusion

Increasingly autonomous and sophisticated algorithmic pricing raises novel challenges to which antitrust enforcers must adapt. Algorithms may facilitate express collusion by making cartels easier to create and maintain. Algorithms could also lead to increased tacit collusion between firms under certain conditions, a prospect against which the Sherman Act offers little protection. If new technologies make coordinated interaction more likely, competition enforcers will need to focus more on coordinated effects in merger analysis at lower market concentration thresholds. Ultimately, it may be necessary to rethink the role of human-focused concepts such as "agreement" under the antitrust laws.

These technologies are also likely to lead to increasingly sophisticated forms of price discrimination. As with algorithmic pricing generally, algorithmic price discrimination has the potential to provide consumer benefits, such as enabling companies to identify and offer discounts to targeted consumers who were previously priced out of certain markets. But price discrimination may also produce narrower antitrust relevant product markets. As we show in our examples, this may increase the chances that a given merger will harm consumers in some relevant market even if the remaining post-merger competition is sufficient to protect the majority of consumers. Under the Guidelines, the agencies normally will not simply abandon particular groups of consumers to a post-merger exercise of market power by trading off potential gains and losses across different relevant markets. But it may be difficult to fashion tailored structural remedies for price discrimination markets defined on the basis of consumer characteristics. Where a merger promises cognizable efficiencies but would enhance market power in one or more narrow price discrimination markets, behavioral remedies may prove to be the best enforcement option. To adequately protect competition, enforcers must continue to examine whether assumptions and practices from the brick-and-mortar world hold true in the digital one. ■

1 The term "robot" was introduced to the English language in 1920 by Czech playwright Karel Čapek's play "Rossum's Universal Robots." Science Diction: The Origin of the Word 'Robot,' NPR (Apr. 22, 2011), http://www.npr.org/2011/04/22/135634400/science-diction-the-origin-of-the-word-robot.

2 Press Release, U.S. Dep't of Justice, Former E-Commerce Executive Charged with Price Fixing in the Antitrust Division's First Online Marketplace Prosecution (Apr. 6, 2015), http://www.justice.gov/opa/pr/former-e-commerce-executive-charged-price-fixing-antitrust-divisions-first-online-marketplace.

3 See Ariel Ezrachi & Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition* 7–9 (Univ. of Oxford Ctr. for Competition Law and Policy, Working Paper CCLP (L) 40, 2015), https://www.law.ox.ac.uk/sites/files/oxlaw/cclpl40.pdf.

4 *See* Brooke Grp. Ltd. v. Brown & Williamson Tobacco Corp., 509 U.S. 209, 227 (1993).

5 Salil K. Mehra, *Antitrust and the Robo-Seller: Competition in the Time of Algorithms*, 100 Minn. L. Rev. 1323, 1352 (2016).

6 Plea Agreement at 3–4, United States v. Topkins, No. 3:15-cr-00201-WHO (N.D. Cal. Apr. 30, 2015).

7 Ariel Ezrachi & Maurice E. Stucke, Virtual Competition: The Promise and Perils of the Algorithm-Driven Economy 39 (2016). Professors Ezrachi and Stucke examine a number of "collusion scenarios" involving algorithms and artificial intelligence in their book. This article discusses two of those scenarios.

8 U.S. Dep't of Justice & Fed. Trade Comm'n, Horizontal Merger Guidelines § 7.2 (2010), http://ftc.gov/os/2010/08/100819hmg.pdf.

9 Margrethe Vestager, Comm'r, Eur. Comm'n, Algorithms and Competition, Remarks at the Bundeskartellamt 18th Conference on Competition, Berlin (Mar. 16, 2017), https://ec.europa.eu/commission/commissioners/2014-2019/vestager/announcements/bundeskartellamt-18th-conference-competition-berlin-16-march-2017_en.

10 The FTC has taken initial steps to expand its in-house expertise by adding an Office of Technology, Research and Investigations staffed with technologists and computer scientists. Press Release, Fed. Trade Comm'n, BCP's Office of Technology Research and Investigation: The Next Generation in Consumer Protection (Mar. 23, 2015), https://www.ftc.gov/news-events/blogs/business-blog/2015/03/bcps-office-technology-research-investigation-next. One can imagine that technological experts will play a greatly expanded role in future cases, both at the FTC and at other competition agencies.

11 Ezrachi & Stucke, *supra* note 7, at 39–42.

12 Vestager, *supra* note 9.

13 Ezrachi & Stucke, *supra* note 7, at 56.

14 Mehra, *supra* note 5, at 1343.

15 This is unsurprising given that similar conditions contribute to explicit and tacit collusion. Indeed, the U.S. antitrust agencies assess the potential for explicit and tacit collusion jointly as "coordinated interaction" under the Guidelines. Guidelines, *supra* note 8, § 7.

16 Mehra, *supra* note 5, at 1340.

17 Ezrachi & Stucke, *supra* note 7, at 62.

18 Bruno Salcedo, Pricing Algorithms and Tacit Collusion 3 (Nov. 1, 2015) (unpublished Ph.D. dissertation, Pennsylvania State University), http://brunosalcedo.com/docs/collusion.pdf. Salcedo assumes a dynamic model in which firms commit to pricing algorithms in the short run but are able to decode their competitors' algorithms over time and periodically revise their own algorithms in response.

19 *Id.* at 5, 20.

20 *Id.* at 4.

21 *See, e.g.*, Ezrachi & Stucke, *supra* note 7, at 36; Mehra, *supra* note 5, at 1340; Vestager, *supra* note 9.

22 Salcedo, *supra* note 18, at 4.

23 *See, e.g.*, Directorate for Fin. and Enter. Affairs Competition Comm., Org. for Econ. Co-operation and Dev., Algorithms and Collusion, DAF/COMP(2017)4 at 37 (2017), https://one.oecd.org/document/DAF/COMP(2017)4/en/pdf.

24 *See, e.g.*, Dennis W. Carlton & Jeffrey M. Perloff, Modern Industrial Organization 296, 299 (4th ed. 2005).

25 Adam Tanner, *Different Customers, Different Prices, Thanks to Big Data*, Forbes (Mar. 26, 2014), http://www.forbes.com/sites/adamtanner/2014/03/26/different-customers-different-prices-thanks-to-big-data/#4706c0a6f31c (quoting Professor John Gourville).

26 Executive Office of the President, Big Data: Seizing Opportunities, Preserving Values 2 (2014), https://obamawhitehouse.archives.gov/sites/default/files/docs/big_data_privacy_report_may_1_2014.pdf.

27 Fed. Trade Comm'n, Data Brokers: A Call for Transparency and Accountability 47 (2014), https://www.ftc.gov/system/files/documents/reports/data-brokers-call-transparency-accountability-report-federal-trade-commission-may-2014/140527databrokerreport.pdf.

28 Candice Choi, *How Grocery Store Loyalty Programs Affect What You Buy, How Much You Spend*, Boston Globe (May 17, 2013), https://www.bostonglobe.com/business/2013/05/16/how-grocery-store-loyalty-programs-affect-what-you-buy-how-much-you-spend/8xTOIirUcBDctXrxSQI3TK/story.html (quoting Steve Burd, CEO of Safeway).

29 It is worth noting that the conditions of "perfect competition" are almost never satisfied in real life, but the model is a useful approximation of what are generally thought of as "competitive" conditions.

30 Ezrachi & Stucke, *supra* note 7, at 101. *See also* Andrew Odlyzko, Privacy, Economics, and Price Discrimination on the Internet 4 (July 27, 2003) (unpublished manuscript), http://www.dtc.umn.edu/~odlyzko/doc/privacy.economics.pdf (explaining that while first-degree price discrimination "has long been treated in the literature as an unattainable ideal . . . [e]rosion of privacy and improved IT systems will enable a close approximation to this ideal to be achieved").

31 *See* Odlyzko, *supra* note 30, at 4, 15 (describing "abundant evidence" from behavioral economics that "[p]eople do not like being subjected to dynamic pricing" and predicting that companies will seek to camouflage online price discrimination "since the public is likely to resent [differential pricing regimes] intensely").

32 *See, e.g.*, Walter Nicholson & Christopher Snyder, Microeconomic Theory: Basic Principles and Extensions 517–19 (11th ed. 2012).

33 *See, e.g.*, ABA Section of Antitrust Law, Market Definition in Antitrust: Theory and Case Studies 5 (2012) ("The success of the Internet-based auction site eBay dramatically lowered the search costs and transaction costs for auction participants and thus may have caused a great number of formerly small geographic markets for resale items, such as antiques, to expand and merge, becoming national or even international in scope.").

34 *See* Michael Cavna, *'Nobody Knows You're a Dog': As Iconic Internet Cartoon Turns 20, Creator Peter Steiner Knows the Idea Is as Relevant as Ever*, Wash. Post (July 31, 2013), https://www.washingtonpost.com/blogs/comic-riffs/post/nobody-knows-youre-a-dog-as-iconic-internet-cartoon-turns-20-creator-peter-steiner-knows-the-joke-rings-as-relevant-as-ever/2013/07/31/73372600-f98d-11e2-8e84-c56731a202fb_blog.html?utm_term=.c250f89cb673

35 Odlyzko, *supra* note 30, at 1.

36 Guidelines, *supra* note 8, § 3.

37 *Id.*

38 *Id.*

39 *See generally* ABA Section of Antitrust Law, *supra* note 33, at 190 (explaining that "[t]he opportunity for firms to profit by differentially charging different customers (on either side of a two-sided market) may disaggregate the relevant market calculated by a single [small but significant and nontransitory increase in price] into separate markets").

40 *See* FTC v. Sysco Corp., 113 F. Supp. 3d 1, 38–48 (D.D.C. 2015).

[41] FTC v. Staples, Inc., 190 F. Supp. 3d 100, 126 (D.D.C. 2016).

[42] Guidelines, *supra* note 8, § 10 n.14.

[43] *Id.*

[44] It is not essential that Firm A have a *unique* capacity to price discriminate. The analytical framework would be the same if multiple (or even all) firms in the market possessed similar capabilities. All that is necessary is that one or more of the firms to which a particular group of consumers can turn, post-merger, is capable of identifying and targeting prices to that specific group. That firm need not even be a merging party. For instance, if Firm C possessed the ability to engage in targeted price discrimination, this would potentially be sufficient to analyze the effects of the merger in a narrow price discrimination market.

[45] The analysis here and in our subsequent examples assumes that entry into the relevant market would not be sufficient or timely enough to deter or counteract any competitive effects.

[46] *See* U.S. Dep't of Agriculture, Economic Research Service, Household Food Access and Vehicle Availability, 2006 and 2010, https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=76318.

[47] As noted *supra* note 44, all that is necessary to potentially define a price discrimination market for product consumers who live in households without a vehicle is for either the merged Firm A or Firm C to have the capability to identify and target prices to that group. At the same time, the identity and number of firms capable of engaging in price discrimination may be relevant to the competitive effects analysis. In Example 1, Firm A will ignore the competitive initiatives of Firms D, E, and F when setting prices for consumers without cars. But if Firm C is not capable of identifying and targeting prices to consumers without cars, Firm C's reaction to competitive initiatives of Firms D, E, and F would likely influence prices for consumers without cars. The extent of this indirect influence would be relevant in determining whether it is appropriate to define a price discrimination market. If, on the other hand, Firm C is also capable of identifying and targeting prices to consumers without cars, the competitive initiatives of Firms D, E, and F would not affect prices in the targeted price discrimination market.

[48] It is not essential to the competitive analysis in this example that all firms have the capability to engage in price discrimination. *See supra* note 44. But note also that algorithm-driven price discrimination is not inherently limited to online sellers. For example, brick-and-mortar retailers can track individual consumers in their stores using cell phone Wi-Fi signals. Stephanie Clifford & Quentin Hardy, *Attention, Shoppers: Store Is Tracking Your Cell*, N.Y. Times (July 14, 2013), http://www.nytimes.com/2013/07/15/business/attention-shopper-stores-are-tracking-your-cell.html. A brick-and-mortar retailer can engage in price discrimination by setting one shelf price and offering differential discounts to individual consumers through their phones or through coupons tied to store loyalty programs.

[49] As noted previously for Examples 1 and 2, the analysis here does not turn on Firm A having a unique ability to price discriminate. *See supra* note 44.

[50] 72% = 0.9 (percentage of consumers with cars) x 0.8 (percentage of politically moderate consumers). The merger would reduce the available options for 18% of consumers from five to four. For 9% of consumers, this would be a 3-to-2 merger. It would be a merger to monopoly for 1% of consumers.

[51] We are by no means suggesting that this is the *only* market in which competitive concerns arise. Indeed, the minimum post-merger HHI for a market with four remaining firms is 2,500—the threshold at which a market is considered "highly concentrated" and (assuming an HHI increase of 200 points or more) at which a merger is "presumed to be likely to enhance market power." Guidelines, *supra* note 8, § 5.3.

[52] Fed. Trade Comm'n, *supra* note 27, at 47.

[53] *See* Guidelines, *supra* note 8, § 10 n.14 ("The Agencies normally assess competition in each relevant market affected by a merger independently and normally will challenge the merger if it is likely to be anticompetitive in any relevant market. In some cases, however, the Agencies in their prosecutorial discretion will consider efficiencies not strictly in the relevant market, but so inextricably linked with it that a partial divestiture or other remedy could not feasibly eliminate the anticompetitive effect in the relevant market without sacrificing the efficiencies in the other market(s).").