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## User-Generated Data Network Effects and Market Competition Dynamics

Uri Y. Hacoen

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## User-Generated Data Network Effects and Market Competition Dynamics

### Cover Page Footnote

\* Professor of Law and Faculty Fellow at the Chief Justice Meir Shamgar Center for Digital Law and Innovation, The Buchmann Faculty of Law, Tel Aviv University. I would like to thank Professors Peter Menell, Niva Elkin-Koren, Michael Birnhack, Amir Khoury, Assaf Hamdani and the participants of the 8th Privacy, Cyber, and Technology Conference at Tel Aviv University, the 2021 Intellectual Property Scholars Conference at Cardozo Law School, and the Lab for Law, Data, and Digital Ethics at Bar-Ilan University.

# User-Generated Data Network Effects and Market Competition Dynamics

Uri Y. Hacoheh\*

*This Article defines User-Generated Data (“UGD”) network effects, distinguishes them from the more familiar concept of traditional network effects, and explores their implications for market competition dynamics. It explains that UGD network effects produce various efficiencies for digital service providers (“data platforms”) by empowering their services’ optimization, personalization, and continuous diversification. In light of these efficiencies, competition dynamics in UGD-driven markets tend to be unstable and lead to the formation of dominant multi-industry conglomerates. These processes will enhance social welfare because they are natural and efficient. Conversely, countervailing UGD network effects also empower data platforms to detect and neutralize competitive threats, price discriminate among users, and manipulate users’ behaviors. The realization of these effects will result in inefficiencies, which will undermine social welfare. After a comprehensive analysis of conflicting economic forces, this Article sets the ground for informed policymaking. It suggests that emerging calls to aggravate antitrust enforcement and to “break up” Big Tech are ill-advised. Instead, this Article calls for policymakers to draw inspiration from traditional network industries’ public utility and open-access regulations.*

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\* Professor of Law and Faculty Fellow at the Chief Justice Meir Shamgar Center for Digital Law and Innovation, The Buchmann Faculty of Law, Tel Aviv University. I would like to thank Professors Peter Menell, Niva Elkin-Koren, Michael Birnhack, Amir Khoury, Assaf Hamdani and the participants of the 8th Privacy, Cyber, and Technology Conference at Tel Aviv University, the 2021 Intellectual Property Scholars Conference at Cardozo Law School, and the Lab for Law, Data, and Digital Ethics at Bar-Ilan University.

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## INTRODUCTION

The fourth muffin is not as delicious as the third, and the second car is less exciting than the first. It is well known that the more goods and services are consumed, the less they are valued. This idea, dubbed the Law of Diminishing Marginal Utility, is a fundamental principle in neoclassical economic theory.<sup>1</sup> Yet modern-day information goods rarely confirm this premise.<sup>2</sup> Netflix’s system

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<sup>1</sup> See Will Kenton, *What is the Law of Diminishing Marginal Utility*, INVESTOPEDIA (Dec. 20, 2022), <https://www.investopedia.com/terms/l/lawofdiminishingutility.asp> [https://perma.cc/JGR7-7XYC]. The concept of diminishing utility has roots in the writings of Aristotle. See Emil Kauder, *Genesis of the Marginal Utility Theory: From Aristotle to the End of the Eighteenth Century*, 63 *ECON. J.* 638, 638 (1953). The concept was first formulized by the German Economist Herman Heinrich Gossen in 1854 and later popularized by Alfred Marshall, who called it the “Law of Satiabale Wants or of Diminishing Utility.” Kepa M. Ormazabal, *The Law of Diminishing Marginal Utility in Alfred Marshall’s Principles of Economics*, 2 *EURO. J. HIST. ECON. THOUGHT* 91, 91 (1995).

<sup>2</sup> See, e.g., SCOTT GALLOWAY, *THE FOUR: THE HIDDEN DNA OF AMAZON, APPLE, FACEBOOK, AND GOOGLE* 105 (Penguin Books 2018) (“We now have a Benjamin Button class of products that age in reverse. Wearing your Nikes makes them less valuable. But posting to Facebook that you are wearing Nikes makes the network more valuable.”). Modern information goods and services become better with usage thanks to developments in data analytics and machine learning technologies. See *infra notes* 59–60 and

becomes more accurate with the more movies we watch,<sup>3</sup> Amazon’s book suggestions become more refined with the more books we purchase,<sup>4</sup> Google search results become more precise the more we inquire,<sup>5</sup> and Facebook’s News Feed becomes more captivating the more we scroll.<sup>6</sup>

These dynamics extend across services and product lines.<sup>7</sup> The more we use Gmail to communicate with friends and colleagues, the more we inadvertently support features such as “Smart Compose”

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accompanying text. Interestingly, long before machine learning, economists noted that “learning” may form an exception to the Law of Diminishing Marginal Utility. *See, e.g.,* ALFRED MARSHAL, *PRINCIPLES OF ECONOMICS* 94 (9th ed. 1961) (“The more good music a man hears, the stronger is his taste for it likely to become.”). In Marshal’s view, for the law to be properly applied, we must “not suppose time to be allowed for any alteration in the character or tastes of the man himself.” *Id.*

<sup>3</sup> *See* Tom Vanderbilt, *The Science Behind the Netflix Algorithms that Decide What You’ll Watch Next*, *WIRED* (Aug. 7, 2013, 6:30 AM), <https://www.wired.com/2013/08/qq-netflix-algorithm/> [<https://perma.cc/2FKM-G5BQ>].

<sup>4</sup> *See* Muffaddal Qutbuddin, *Comprehensive Guide on Item Based Collaborative Filtering*, *MEDIUM* (Mar. 7, 2020), <https://towardsdatascience.com/comprehensive-guide-on-item-based-recommendation-systems-d67e40e2b75d> [<https://perma.cc/3QFN-LJJ6>] (“Item-item collaborative filtering . . . was developed by Amazon in 1998 and plays a great role in Amazon’s success.”).

<sup>5</sup> *See* Cédric Argenton & Jens Prüfer, *Search Engine Competition with Network Externalities*, 8 *J. COMPETITION L. & ECON.* 73, 74–75 (2012) (“Access to more search log data today leads to higher perceived search quality.”); Pamela Jones Harbour & Tara Isa Koslov, *Section 2 in a Web 2.0 World: An Expanded Vision of Relevant Product Markets*, 76 *ANTITRUST L.J.* 769, 777 (2010); *see also* FABRIZIO SILVESTRI, *MINING QUERY LOGS: TURNING SEARCH USAGE DATA INTO KNOWLEDGE* 3 (2010); David S. Evans, *The Economics of the Online Advertising Industry*, 7 *REV. NETWORK ECON.* 359, 373 (2008); James Grimmelman, *The Structure of Search Engine Law*, 93 *IOWA L. REV.* 1, 10–11 (2007); Tiffani Wroe, *How Google Search (Probably) Uses Machine Learning*, *EMBEDDED COMPUTING DESIGN* (Nov. 14, 2019), <https://www.embedded-computing.com/guest-blogs/how-google-search-probably-uses-machine-learning> [<https://perma.cc/V5RN-ANYE>]; Matthew Capala, *Machine Learning Just Got More Human with Google’s RankBrain*, *NEXT WEB* (Sept. 2, 2016), <https://thenextweb.com/artificial-intelligence/2016/09/02/machine-learning-just-got-more-human-with-googles-rankbrain/> [<https://perma.cc/7R3V-MM4S>].

<sup>6</sup> *See* Akos Lada et al., *How Machine Learning Powers Facebook’s News Feed Ranking Algorithm*, *ENG’G AT META* (Jan. 26, 2021), <https://engineering.fb.com/2021/01/26/ml-applications/news-feed-ranking/> [<https://perma.cc/J8WU-2ANB>]; Avantika Monnappa, *How Facebook Is Using Big Data—The Good, the Bad, and the Ugly*, *SIMPLILEARN*, <https://www.simplilearn.com/how-facebook-is-using-big-data-article> [<https://perma.cc/6BPD-BAHL>].

<sup>7</sup> *See* discussion *infra* Section II.B.

and “Smart Reply,” which help improve Gmail services.<sup>8</sup> At the same time, we also improve other Google products, such as search, autocomplete, and—until 2017—targeted advertising.<sup>9</sup> According to one of Google’s patent applications, smart home devices could soon utilize the information they gather in one context (e.g., recognizing a T-shirt bearing Cate Blanchett’s face) to provide better services in another context (e.g., recommending a newly released film starring Cate Blanchett).<sup>10</sup>

To explain these unprecedented economic dynamics, this Article applies the traditional theory of network effects to the aggregation and analysis of user-generated data (“UGD” or “data”).<sup>11</sup> Network effects traditionally apply to situations where the value of products or services—usually communication devices such as phones—increases as more users purchase the product or join the service.<sup>12</sup>

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<sup>8</sup> See Bálint Miklós, *Computer, Respond to This Email: Introducing Smart Reply in Inbox by Gmail*, GOOGLE: THE KEYWORD (Nov. 3, 2015), <https://blog.google/products/gmail/computer-respond-to-this-email/> [<https://perma.cc/5C66-MTPU>] (“[T]he responses you choose (or don’t choose!) help improve future suggestions.”); Jillian D’Onfro & Jordan Novet, *Gmail Will Soon Be Able to Finish Some Sentences for You*, CNBC (May 8, 2018), <https://www.cnbc.com/2018/05/08/google-launches-smart-compose-for-gmail.html> [<https://perma.cc/ME7J-KTT3>].

<sup>9</sup> See Ben Popken, *Google Sells the Future, Powered by Your Personal Data*, NBC NEWS (May 10, 2018), <https://www.nbcnews.com/tech/tech-news/google-sells-future-powered-your-personal-data-n870501> [<https://perma.cc/DT4P-JHRD>]; Steven Levy, *How Google Is Remaking Itself as a “Machine Learning First” Company*, WIRED (June 22, 2016), <https://www.wired.com/2016/06/how-google-is-remaking-itself-as-a-machine-learning-first-company/> [<https://perma.cc/6QQD-Q3WE>]; Nick Statt, *Google Will Stop Scanning Your Gmail Messages to Sell Targeted Ads*, VERGE (June 23, 2017), <https://www.theverge.com/2017/6/23/15862492/google-gmail-advertising-targeting-privacy-cloud-business> [<https://perma.cc/99VG-S4LH>].

<sup>10</sup> See Sapna Maheshwari, *Hey, Alexa, What Can You Hear? And What Will You Do With It?*, N.Y. TIMES (Mar. 31, 2018), <https://www.nytimes.com/2018/03/31/business/media/amazon-google-privacy-digital-assistants.html> [<https://perma.cc/V9FR-MNN8>].

<sup>11</sup> See discussion *infra* Part I; see also TOM SYMONS & THEO BASS, *ME, MY DATA AND I: THE FUTURE OF THE PERSONAL DATA ECONOMY* 24 (2017) <https://media.nesta.org.uk/documents/decode-02.pdf> [<https://perma.cc/G7Z7-4UTR>] (“The internet economy is itself difficult to understand with conventional economic theory.”).

<sup>12</sup> See *infra* note 44 and accompanying text.

Metcalfe’s Law—named after Bob Metcalfe, the co-inventor of the Ethernet—states that a network’s value is proportional to the square number of users connected to it ( $n^2$ ).<sup>13</sup> Therefore, by doubling the number of phone users (e.g., from 10 to 20), a telephone network more than quadruples its value because it increases the number of possible connections between users (e.g., from 45 to 190).<sup>14</sup> Traditional network effects focus on the relationship between a network’s value and the number of network users. In contrast, UGD network effects focus on the relationship between the network’s value and the volume, variety, and velocity of data the network’s users generate.<sup>15</sup> Thus, by doubling its UGD supply, a company such as Google can drastically increase its capacity to improve existing goods and services, as well as create new ones entirely.<sup>16</sup>

This Article defines and models UGD network effects, distinguishes them from traditional network effects, and accounts for their impact on market competition dynamics and social welfare. Some scholars investigating this topic have dismissed UGD network effects as a nonexistent or irrelevant economic phenomenon,<sup>17</sup> while

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<sup>13</sup> See CARL SHAPIRO & HAL R. VARIAN, INFORMATION RULES: A STRATEGIC GUIDE TO THE NETWORK ECONOMY 184 (1999).

<sup>14</sup> In practice, not all the added users have an equal weight within the network as assumed by Metcalfe’s Law. See Bob Briscoe et al., *Metcalfe’s Law Is Wrong*, IEEE SPECTRUM (July 1, 2006), <https://spectrum.ieee.org/computing/networks/metcalfes-law-is-wrong> [<https://perma.cc/78S2-YQRN>]. Still, Metcalfe’s Law is used as a rough empirical approximation, which is helpful in modeling the increasing value mandated by network effects. See *id.*

<sup>15</sup> See *infra* note 58 and accompanying text.

<sup>16</sup> See *infra* note 58 and accompanying text; see also OECD, DATA-DRIVEN INNOVATION FOR GROWTH AND WELL-BEING: INTERIM SYNTHESIS REPORT 26–27 (2014) [hereinafter DATA-DRIVEN INNOVATION] (“[In] theory there is no limitation for what purposes data can be used . . .”).

<sup>17</sup> See Hal R. Varian, *Use and Abuse of Network Effects*, in TOWARD A JUST SOCIETY: JOSEPH STIGLITZ AND TWENTY-FIRST CENTURY ECONOMICS, 227–39 (Martin Guzman ed., 2018) [hereinafter Varian, *Use and Abuse*] (dismissing UGD network effects as “learning by doing”); Hal. R. Varian, *Recent Trends in Concentration, Competition, and Entry*, 82 ANTITRUST L.J. 807, 826 (2019) [hereinafter Varian, *Recent Trends*]; see also Robert H. Bork & J. Gregory Sidak, *What Does the Chicago School Teach About Internet Search and the Antitrust Treatment of Google?*, 8 J. COMPETITION L. & ECON. 663, 687–92 (2012); Geoffrey A. Manne & Joshua D. Wright, *Google and the Limits of Antitrust: The Case Against the Antitrust Case Against Google*, 34 HARV. J.L. & PUB. POL’Y 3, 36–37 (2011).

others have framed UGD network effects as a source of anticompetitive harm.<sup>18</sup> This Article follows a more holistic approach.<sup>19</sup>

Part I defines UGD network effects as an important and socially beneficial phenomenon.<sup>20</sup> As this Part explains, developments in data analytics and machine learning technologies allow businesses to leverage UGD to optimize, personalize, and diversify their services to benefit users. For example, utilizing these technologies, Google developed its email service, Gmail, into what is now known as Google Workspace: a fully integrated productivity environment

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<sup>18</sup> See LIZA LOVDAHL GORMSEN & JOSE TOMAS LLANOS, FACEBOOK'S ANTICOMPETITIVE LEAN IN STRATEGIES 61 (2019), [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3400204](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3400204) [<https://perma.cc/VZ45-VD5Y>]; AMNESTY INT'L, SURVEILLANCE GIANTS: HOW THE BUSINESS MODEL OF GOOGLE AND FACEBOOK THREATENS HUMAN RIGHTS 42 (2019) [hereinafter AMNESTY INT'L]; STIGLER CTR. FOR STUDY ECON. & STATE, STIGLER COMMITTEE ON DIGITAL PLATFORMS: FINAL REPORT 40 (2019) [hereinafter STIGLER FINAL REPORT], <https://www.chicagobooth.edu/-/media/research/stigler/pdfs/digital-platforms-committee-report---stigler-center.pdf> [<https://perma.cc/EW4V-YXUM>]; DIG. COMPETITION EXPERT PANEL, UNLOCKING DIGITAL COMPETITION 33 (2019) [hereinafter DIG. COMPETITION], [https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment\\_data/file/785547/unlocking\\_digital\\_competition\\_furman\\_review\\_web.pdf](https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/785547/unlocking_digital_competition_furman_review_web.pdf) [<https://perma.cc/73FS-EMUS>]; STAFF OF SUBCOMM. ON ANTITRUST, COM. AND ADMIN. L., 117TH CONG., INVESTIGATION OF COMPETITION IN DIGITAL MARKETS 42 (Comm. Print 2020) [hereinafter SUBCOMM., INVESTIGATION OF COMPETITION]; JACQUES CRÉMER ET AL., DIRECTORATE-GENERAL FOR COMPETITION, EUROPEAN COMM'N, COMPETITION POLICY FOR THE DIGITAL ERA 31 (2019), <https://ec.europa.eu/competition/publications/reports/kd0419345enn.pdf> [<https://perma.cc/T9RW-P477>]; MAURICE E. STUCKE & ALLEN P. GRUNES, BIG DATA AND COMPETITION POLICY 170 (2016); DATA-DRIVEN INNOVATION, *supra* note 16, at 10, 29; Michal S. Gal & Daniel L. Rubinfeld, *Data Standardization*, 94 N.Y.U. L. REV. 737, 758 (2019); Daniel McIntosh, *We Need to Talk About Data: How Digital Monopolies Arise and Why They Have Power and Influence*, 23 J. TECH. L. & POL'Y 185, 193 (2019).

<sup>19</sup> Cf. Richard T. Ford, *Save the Robots: Cyber Profiling and Your So-Called Life*, 52 STAN. L. REV. 1573, 1575 (2000) (“The concerns I’m about to raise . . . could be interpreted as a positive advance.”); Joshua A.T. Fairfield & Christoph Engel, *Privacy as a Public Good*, 65 DUKE L.J. 385, 398 (2015) (“[I]nformation produces both positive and negative network effects, and both positive and negative externalities.”); Jane Y. Bambauer, *The New Intrusion*, 88 NOTRE DAME L. REV. 205, 227 (2012) (“[P]rivacy losses are the negative externalities from an otherwise productive and worthwhile activity—information flow.”).

<sup>20</sup> See *infra* Part I.



that includes a calendar, spreadsheet function, file storage, and video communication.<sup>21</sup>

Part II builds on these efficiencies and explores how UGD network effects affect market competition dynamics.<sup>22</sup> It explains that, similar to markets characterized by traditional network effects, multi-company competition in UGD-driven markets is usually unstable and may result in market “tipping” in favor of companies with more significant UGD aggregation and analytics capabilities.<sup>23</sup> This dynamic contributes to the emerging dominance of large data platforms in markets, such as web search engines (e.g., Google), social media platforms (e.g., Meta), and e-commerce sites (e.g., Amazon).<sup>24</sup> This Part further explains that, unlike traditional network effect markets, when UGD network effects are present, the same tipping tendencies are likely to expand across different market categories and give rise to a new generation of prosperous multi-industry conglomerates.<sup>25</sup> For example, consider Alphabet’s expansion from the web-search market to equipment manufacturing, autonomous driving, biomedical research, and more.<sup>26</sup>

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<sup>21</sup> See Kelly Waldher & Aparna Pappu, *Google Workspace for Everyone*, GOOGLE: KEYWORD (June 14, 2021), <https://blog.google/products/workspace/google-workspace-everyone/> [<https://perma.cc/TM5W-E2B2>]; *How Machine Learning in G Suite Makes People More Productive*, GOOGLE: THE KEYWORD (May 4, 2017), <https://blog.google/products/g-suite/how-machine-learning-g-suite-makes-people-more-productive/> [<https://perma.cc/L242-VPU4>] (emphasizing the role of UGD and machine-learning); see also Charlie Warzel & Ash Ngu, *Google’s 4,000-Word Privacy Policy Is a Secret History of the Internet*, N.Y. TIMES (July 10, 2019), <https://www.nytimes.com/interactive/2019/07/10/opinion/google-privacy-policy.html> [<https://perma.cc/4H87-WDV3>] (“[Google] may share the information submitted under your account among all of our services in order to provide you with a seamless experience and to improve the quality of [Google’s] services.”).

<sup>22</sup> See *infra* Part II.

<sup>23</sup> See *infra* Section II.A.

<sup>24</sup> See GALLOWAY, *supra* note 2, at 61; see also CRÉMER ET AL., *supra* note 18, at 12–13.

<sup>25</sup> See *infra* Section II.B; see also MARCO IANSITI & KARIM R. LAKHANI, *COMPETING IN THE AGE OF AI: STRATEGY AND LEADERSHIP WHEN ALGORITHMS AND NETWORKS RUN THE WORLD* 176 (2020); *DATA-DRIVEN INNOVATION*, *supra* note 16, at 15.

<sup>26</sup> See Avery Hartmans & Mary Meisenzahl, *All the Companies and Divisions Under Google’s Parent Company, Alphabet, Which Just Made Yet Another Shake-Up to its Structure*, BUS. INSIDER (Feb. 12, 2020), <https://www.businessinsider.com/alphabet-google-company-list-2017-4> [<https://perma.cc/R CZ8-427Q>].

Lastly, Part II explains that unlike traditional network effect markets, competition for entire markets (also known as “creative destruction”) is unlikely to occur in the presence of UGD network effects.<sup>27</sup> Incumbent data platforms have greater access to UGD analytics than their nascent competitors, meaning the former are more likely to absorb and improve on the latter than the latter is to disrupt and displace the former.<sup>28</sup> For example, Facebook—unlike its archrival ancestor Myspace—has successfully prevented several disruption attempts by reinventing itself in the face of numerous competitive challenges.<sup>29</sup>

Part III explores the welfare implications of these dynamics, given countervailing adverse effects.<sup>30</sup> It explains that while UGD-driven consolidation unlocks significant economic efficiencies, the loss of disciplining market forces undermines these efficiencies over time. First, because data platforms can use UGD-driven intelligence to detect, neutralize, or outperform “disruptive” threats, they will not face pressure to continue innovating.<sup>31</sup> As a result, innovation might stagnate. Second, even if incumbent data platforms function as innovation powerhouses, they could leverage massive information asymmetry to engage in price discrimination and behavioral

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<sup>27</sup> See *infra* Section II.C.

<sup>28</sup> See *infra* Section II.C.

<sup>29</sup> Consider how Facebook (now Meta) copied and potentially utilized UGD to improve upon Snapchat’s original “Stories” feature when launching a similar “Story” feature on Instagram. See Kurt Wagner, *Inside Instagram’s Reinvention*, VOX (Jan. 23, 2017), <https://www.vox.com/2017/1/23/14205686/instagram-product-launch-feature-kevin-systrom-weil> [<https://perma.cc/8S86-4MU2>]; Uptin Saiidi & Javier E. David, *Instagram Encroaches on Snapchat’s Turf of Social Media Influencers, Winning Their Hearts, Minds and Posts*, CNBC (July 22, 2017), <https://www.cnbc.com/2017/07/22/snapchat-or-instagram-stories-whats-a-social-media-influencer-to-do.html> [<https://perma.cc/9A35-VDVY>]. For instance, Instagram used UGD-driven analytics to identify user demand for a “re-sharing” feature in 2016 and subsequently incorporated this feature to their system in 2018. See Kurt Wagner, *‘Stories’ was Instagram’s Smartest Move Yet*, VOX (Aug. 8, 2018), <https://www.vox.com/2018/8/8/17641256/instagram-stories-kevin-systrom-facebook-snapchat> [<https://perma.cc/2G9Q-3L5A>]; *Introducing @mention Sharing for Instagram Stories*, INSTAGRAM BLOG (June 7, 2018), <https://about.instagram.com/blog/announcements/introducing-mentions-sharing-for-instagram-stories> [<https://perma.cc/T4DM-J7ZV>]; see also C. Scott Hemphill, *Disruptive Incumbents: Platform Competition in an Age of Machine Learning*, 119 COLUM. L. REV. 1974, 1996 (2019) (explaining how Facebook innovated in reaction to Google+).

<sup>30</sup> See *infra* Part III.

<sup>31</sup> See *infra* Section III.A.

manipulation.<sup>32</sup> Price discrimination is economically efficient but has disturbing moral and distribution implications for users—especially those that are most vulnerable.

Behavioral manipulation is even worse.<sup>33</sup> Data platforms engage in two types of behavioral manipulation. The first type maximizes user demand for products, services, and advertisements.<sup>34</sup> It reduces user welfare directly by inflating demand and indirectly by triggering ancillary harms, such as addiction, depression, and extremism.<sup>35</sup> The second type is an unintentional side effect of the data platforms' optimization and personalization practices. Consider the clueless drivers whom Waze directs off-road to explore uncharted nearby territories or the recovering mentally ill individuals to whom YouTube continues to serve violent content based on their previous interests.<sup>36</sup> This type of latent manipulation also reduces welfare by compromising user autonomy.<sup>37</sup>

Lastly, although all three countervailing effects—innovation hindrance, price discrimination, and behavioral manipulation—have inherent negative implications for user welfare, they can also reduce user welfare by design.<sup>38</sup> These effects may empower data platforms to extend their monopoly across markets and make a profit even without realizing UGD-driven efficiencies. For example, Meta was accused of acquiring Onavo for the purpose of surveilling and neutralizing Meta's competitors,<sup>39</sup> rather than to use the service's UGD "to improve Facebook products and services, gain insights into the products and services people value, and build better experiences," as declared in Onavo's privacy statement.<sup>40</sup>

Finally, this Article concludes by explaining why UGD network effects are essential for technological development and economic

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<sup>32</sup> See *infra* Sections III.B, III.C.

<sup>33</sup> See *infra* Section III.C.

<sup>34</sup> See *infra* Section III.C.

<sup>35</sup> See *infra* Section III.C.

<sup>36</sup> See *infra* Section III.C.

<sup>37</sup> See *infra* Section III.C.

<sup>38</sup> See *infra* notes 252, 270, 299 and accompanying text.

<sup>39</sup> Lily Hay Newman, *Don't Trust the VPN Facebook Wants You to Use*, WIRED (Feb. 15, 2018) <https://www.wired.com/story/facebook-onavo-protect-vpn-privacy/> [<https://perma.cc/N7KF-JCFA>] (citing Onavo's privacy statement).

<sup>40</sup> *Id.*

growth. Although Lina Khan, the current chair of the Federal Trade Commission, has argued against this idea, this Article argues that there is no *a priori* reason to separate “platforms and commerce” in the UGD-driven economy.<sup>41</sup> Nor is it sensible to prescribe *ex-post* divestiture remedies in such cases.<sup>42</sup> Instead, policymakers should draw inspiration from traditional network industries’ public utility and open-access regulations.

### I. DEFINITION AND EFFICIENCIES

*We don’t have better algorithms than anyone else;  
we just have more data.*<sup>43</sup>

*Peter Norvig  
Chief Scientist, Google*

Traditional economic network effects describe situations in which a consumer’s value of a good increases when others also consume that same good.<sup>44</sup> The archetypal example of network goods

<sup>41</sup> See Lina M. Khan, *The Separation of Platforms and Commerce*, 119 COLUM. L. REV. 973, 978 (2019).

<sup>42</sup> See Paula Dwyer, *Should America’s Tech Giants Be Broken Up?*, BLOOMBERG (July 20, 2017), <https://www.bloomberg.com/news/articles/2017-07-20/should-america-s-tech-giants-be-broken-up> [<https://perma.cc/LJN6-YEAT>]; Jonathan Taplin, *Is It Time to Break Up Google?*, N.Y. TIMES (Apr. 22, 2017), <https://www.nytimes.com/2017/04/22/opinion/sunday/is-it-time-to-break-up-google.html> [<https://perma.cc/6YAN-SWQ5>].

<sup>43</sup> See Scott Cleland, *Google’s “Infringnovation” Secrets*, FORBES (Oct. 3, 2011), <https://www.forbes.com/sites/scottcleland/2011/10/03/googles-infringnovation-secrets/> [<https://perma.cc/36P6-DG6Q>] (citing Google’s Chief Scientist Peter Norvig at Google’s Zeitgeist 2011).

<sup>44</sup> See Michael L. Katz & Carl Shapiro, *Network Externalities, Competition, and Compatibility*, 75 AM. ECON. REV. 424, 424 (1985) [hereinafter Katz & Shapiro, *Network Externalities*] (“[T]he utility that a user derives from consumption of a good increases with the number of other agents consuming the good.”); Philip H. Dybvig & Chester S. Spatt, *Adoption Externalities as Public Goods*, 20 J. PUB. ECON. 231, 231–32 (1983); SHAPIRO & VARIAN, *supra* note 13, at 174–75; Mark A. Lemley & David McGowan, *Could Java Change Everything? The Competitive Property of a Proprietary Standard*, 43 ANTITRUST BULL. 715, 719 (1998). The concept of traditional (also known as “direct”) network effects was introduced into economic theory by the early works of Roland Artle, Christian Averous, and Jeffrey Rohlfs. See Roland Artle & Christian Averous, *The Telephone System as a Public Good: Static and Dynamic Aspects*, 4 BELL J. ECON. & MAN. SCI. 89, 90 (1973); Jeffrey Rohlfs, *A Theory of Interdependent Demand for a Communications Service*, 5 BELL

is a telecommunication device, such as the telephone.<sup>45</sup> Owning the only telephone in the world would be valueless to the owner (other than perhaps to serve as a paperweight).<sup>46</sup> However, the telephone's

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J. ECON. & MAN. SCI. 16, 16 (1974). Economic literature also recognizes indirect (or market-mediated) network effects alongside traditional network effects. For example, the value of the Microsoft Windows operating system to a single user increases when other users adopt the system. This is not merely because users can transfer compatible files or easily transmit between jobs. Instead, as more users embrace the operating system, there is an increase in the incentive for third-party developers to create Windows-compatible applications; employers to construct Windows-compatible working environments; and technicians to offer maintenance and support services for Windows—all of which increase the value of Windows to users. In other words, the growing availability of Windows-compatible applications and services indirectly enhances Windows' value to users by promising them broader and longer-lasting functionality. See Nicholas Economides, *The Economics of Networks*, 14 INT'L J. INDUS. ORG. 673, 679 (1996) ("An extra customer yields indirect externalities to other customers, by increasing the demand for components of types A and B."); David J. Teece & Mary Coleman, *The Meaning of Monopoly: Antitrust Analysis in High-Technology Industries*, 43 ANTITRUST BULL. 801, 814 (1998); *United States v. Microsoft Corp.*, 84 F. Supp. 2d 9, 20 (D.D.C. 1999) (recognizing that Microsoft enjoys indirect network effects); Mark A. Lemley & David McGowan, *Legal Implications of Network Economic Effects*, 84 CAL. L. REV. 479, 491–94 (1998) [hereinafter Lemley & McGowan, *Legal Implications*]; Michael L. Katz & Carl Shapiro, *Systems Competition and Network Effects*, 8 J. ECON. PERSP. 93, 99 (1994) [hereinafter Katz & Shapiro, *Systems Competition*]; Gregory J. Werden, *Network Effects and Conditions of Entry: Lessons from the Microsoft Case*, 69 ANTITRUST L.J. 87, 93–94 (2001); Mark A. Lemley & David W. O'Brien, *Encouraging Software Reuse*, 49 STAN. L. REV. 255, 287 (1997); Howard A. Shelanski & J. Gregory Sidak, *Antitrust Divestiture in Network Industries*, 68 CHI. L. REV. 1, 8 (2001); DOUGLAS G. BAIRD ET AL., *GAME THEORY AND THE LAW* 208–13 (1994). While both direct and indirect network effects have similar market dynamics, economists consider them as an analytically distinct phenomenon. See Daniel F. Spulber, *Unlocking Technology: Antitrust and Innovation*, 4 J. COMPETITION L. & ECON. 915, 924 (2008) ("[D]espite frequent claims to the contrary, indirect network effects cannot be a source of market failure leading to technology lock-in."); Stan J. Liebowitz & Stephen E. Margolis, *Network Externality: An Uncommon Tragedy*, 8 J. ECON. PERSP. 133, 139 (1994) [hereinafter Liebowitz & Margolis, *Network Externality*] ("The concept of indirect network externalities . . . is not an externality in the modern sense where it describes nothing more than welfare-neutral interactions that occur in properly functioning markets.").

<sup>45</sup> See Liebowitz & Margolis, *Network Externality*, *supra* note 44, at 139–40 ("The paradigmatic case for a direct network effect . . . is the network of telephone users."); Katz & Shapiro, *Network Externalities*, *supra* note 44, at 424–25 (limiting their discussion of direct network effects to communications technologies); see also Artle & Averous, *supra* note 44.

<sup>46</sup> As AT&T's president, Theodore Vail, famously stated in the company's 1908 annual shareholder report: "[A] telephone—without a connection at the other end of the line—is not even a toy or a scientific instrument. It is one of the most useless things in the world. Its value depends on the connection with the other telephone—and increases with the

value to that owner would continuously increase as others purchase telephones and become more interconnected and reachable through the network.<sup>47</sup>

Network effects result from positive economic externalities that represent the value that users inadvertently share with one another.<sup>48</sup>

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number of connections.” MATTHEW HINDMAN, *THE INTERNET TRAP: HOW THE DIGITAL ECONOMY BUILDS MONOPOLIES AND UNDERMINES DEMOCRACY* 17 (2018).

<sup>47</sup> Assuming, of course, that the phones are interoperable with one another and the network infrastructure can readily support the added traffic. See Lemley & McGowan, *Legal Implications*, *supra* note 44, at 488–89.

<sup>48</sup> An economic externality occurs when a decision maker does not confront, or bear, the full cost or benefits of his economic action. See generally STAN J. LIEBOWITZ & STEPHEN E. MARGOLIS, *WINNERS, LOSERS, & MICROSOFT: COMPETITION AND ANTITRUST IN HIGH TECHNOLOGY* (1999). Externalities may lead to an economic inefficiency of two opposite kinds. Negative externalities create a perverse incentive to overuse, and positive externalities create a perverse incentive to underuse. For a negative externality, consider a factory owner who does not bear the costs that his polluting factory imposes on a nearby farm. Unless the factory owner will bear these costs, she will have the perverse over-incentive to pollute. The economic externalities imposed by traditional network effects are usually positive, not negative. See Liebowitz & Margolis, *Network Externality*, *supra* note 44, at 134; Shelanski & Sidak, *supra* note 44, at 7–8. Alternatively, consider a new telephone user who does not reap the benefits that his connection to the telephone network gives to users. Mirroring the logic of the factory example, unless the telephone user bears such benefits, she will have the perverse under-incentive to interconnect. That user might, therefore, refuse to pay the amount charged for a telephone connection (which in a perfectly competitive market is assumed to be offered at cost), even if the collective benefit that all the network members derive from her participation justifies that price. See Katz & Shapiro, *Systems Competition*, *supra* note 44, at 96. In both cases, economic externalities may lead to a market failure. While the negative externality in the factory example leads to pollution levels that are inefficiently large, the positive externality in the telephone example leads to network interconnection levels that are inefficiently small. See Liebowitz & Margolis, *Network Externality*, *supra* note 44, at 139–140. Economic externalities (positive and negative) can be internalized in many ways. One way is through a contract among market participants, as Ronald Coase famously suggested. See Ronald H. Coase, *The Problem of Social Cost*, 3 J.L. & ECON. 1, 15 (1960). Another way is through government regulation, fees, or tradeable rights. See, e.g., PETER S. MENELL & RICHARD B. STEWART, *ENVIRONMENTAL LAW AND POLICY* 67–70 (1994). Finally, economic externalities can also be internalized through common ownership. In the negative externality example, if the factory owner also owned the farm, then the interests of the two previously separated businesses would align, creating an incentive for the factory owner to reduce the factory’s pollution level to the social optimum. The same is true for the positive externality example. If there is an owner of a telephone network, that owner will be willing to “sponsor” that network by investing resources in its growth. One way to do so would be to reduce the price of accessing the network, even to below operating costs, and then to recover for these initial losses by charging usage fees when the network grows in size. See Liebowitz & Margolis, *Network Externality*, *supra* note 44, at 141; Richard A. Posner, *Antitrust in the*

Networked goods generate some value that consumers cannot fully enjoy themselves, which is then externalized to other consumers. A single Microsoft Word user gains some value from the word processing software because it enables her to edit and format text documents. But that same user also benefits from the many other users who purchased and used Microsoft Word software before them.<sup>49</sup> Perhaps she benefits from exchanging Word files quickly with her colleagues without requiring a conversion program or switching to a different job without needing to master a new word processing software.<sup>50</sup> The more significant the portion of the good's value that is shared with other consumers, the more substantial the network effect.<sup>51</sup>

Depending on the market and business environment, network value can be limited to one product or extended to many.<sup>52</sup> Microsoft Word users derive greater network benefits when other users utilize Microsoft Word, rather than Apple Pages or Apache OpenOffice

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*New Economy*, 68 ANTITRUST L.J. 925, 929 (2000). Thus, in the absence of network ownership, the market might underinvest in the creation of costly networks, and these networks may remain inefficiently small, or may not emerge at all. A similar economic justification applies to intellectual property rights, such as patents. See Joseph Farrell, *Creating Local Competition*, 49 FED. COMM. L.J. 201, 203–04 (1996) (comparing patent economics with network externalities); Katz & Shapiro, *Systems Competition*, *supra* note 44, at 102–03. For this reason, because data platforms “own” UGD (in the sense that they can effectively exclude), they internalize and are thus incentivized to realize positive UGD network externalities. However, data platforms do not internalize various negative UGD network externalities. See discussion *infra* Part III.

<sup>49</sup> See SUZANNE SCOTCHMER, *INNOVATION AND INCENTIVES* 289 (2004) (“[A]n example of a good with network benefits is text-editing software. The value to each user is greater if he or she can share files with other users.”).

<sup>50</sup> See, e.g., Lemley & McGowan, *Legal Implications*, *supra* note 44, at 488. Computer software (operating systems) also produce indirect network effects. See *supra* note 44 and accompanying text; Peter S. Menell, *Tailoring Legal Protection for Computer Software*, 39 STAN. L. REV. 1329, 1341–44 (1987); Lemley & O’Brien, *supra* note 44, at 287–88.

<sup>51</sup> To analyze network effects, scholars often separate the value of network goods into its networked and non-networked portions. See Stan J. Liebowitz & Stephen E. Margolis, *Network Effects and Externalities*, in *THE NEW PALGRAVE DICTIONARY OF ECONOMICS AND THE LAW* 671, 671 (Palgrave 2017) (using the terms “autarky” and “synchronization” values); Lemley & McGowan, *Legal Implications*, *supra* note 44, at 488 (using the terms “inherent” and “network”).

<sup>52</sup> See Joseph Farrell & Garth Saloner, *Standardization, Compatibility, and Innovation*, 16 RAND J. ECON. 70, 71 (1985); Katz & Shapiro, *Network Externalities*, *supra* note 44, at 424.

Writer.<sup>53</sup> Conversely, mobile phone users gain a network benefit regardless of whether other users use an iPhone, a Samsung, or a Blackberry.<sup>54</sup> The criteria for evaluating whether different products provide the same network benefit is whether these products are interconnected (also known as “compatible”).<sup>55</sup> Traditional networks are usually depicted as a web of “nodes,” representing the individual products owned by consumers, which are connected to one another via network “links.”<sup>56</sup> Links can have a physical infrastructure (e.g., copper wires that support telephone systems) or a virtual infrastructure (e.g., technical standards that govern the compatibility of the Microsoft Word format).<sup>57</sup>

UGD network effects, as defined here, describe situations in which the value that users derive from a data platform’s services increases when they invest more UGD in that platform.<sup>58</sup> Data

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<sup>53</sup> See, e.g., *Sharing Files with Microsoft Office Users*, APACHE OPENOFFICE WIKI, [https://wiki.openoffice.org/wiki/Documentation/OOoAuthors\\_User\\_Manual/Migration\\_Guide\\_2006/Sharing\\_Files#:~:text=\(OpenOffice.org%201.1.,extensions%20are%20shown%20in%20brackets\).&text=OpenOffice.org%20can%20open%20Microsoft,not%20open%20OpenOffice.org%20formats](https://wiki.openoffice.org/wiki/Documentation/OOoAuthors_User_Manual/Migration_Guide_2006/Sharing_Files#:~:text=(OpenOffice.org%201.1.,extensions%20are%20shown%20in%20brackets).&text=OpenOffice.org%20can%20open%20Microsoft,not%20open%20OpenOffice.org%20formats) [https://perma.cc/2UEJ-2QTY] (last modified Feb. 15, 2021) (“at this time, Microsoft Office can not open OpenOffice.org formats.”). OpenOffice Writer is partly compatible with Microsoft Word because it can read Doc/Docx files. Nevertheless, files must be converted to work properly between the two systems. See *id.*; *Is OpenOffice compatible with MS Office and StarOffice File Formats?*, APACHE OPENOFFICE WIKI, [https://wiki.openoffice.org/wiki/Documentation/FAQ/General/Is\\_OpenOffice.org\\_compatible\\_with\\_MS\\_Office\\_and\\_StarOffice\\_file\\_formats%3F#:~:text=FAQ%E2%80%8E%20%7C%20General-.Is%20OpenOffice%20compatible%20with%20MS%20Office%20and%20StarOffice%20file%20formats,and%20saved%20by%20Apache%20OpenOffice.](https://wiki.openoffice.org/wiki/Documentation/FAQ/General/Is_OpenOffice.org_compatible_with_MS_Office_and_StarOffice_file_formats%3F#:~:text=FAQ%E2%80%8E%20%7C%20General-.Is%20OpenOffice%20compatible%20with%20MS%20Office%20and%20StarOffice%20file%20formats,and%20saved%20by%20Apache%20OpenOffice.) [https://perma.cc/T7CA-5NXU] (last modified July 22, 2022) (noting that the compatibility between OpenOffice and Microsoft Office’s file formats is “not total”).

<sup>54</sup> Assuming, of course, that they are both servable on the same network.

<sup>55</sup> See Katz & Shapiro, *Network Externalities*, *supra* note 44, at 424.

<sup>56</sup> See Daniel F. Spulber & Christopher S. Yoo, *Mandating Access to Telecom and the Internet: The Hidden Side of Trinko*, 107 COLUM. L. REV. 1822, 1876 (2007) (hereinafter Spulber & Yoo, *Mandating Access*); Daniel F. Spulber & Christopher S. Yoo, *On the Regulation of Networks as Complex Systems: A Graph Theory Approach*, 99 NW. U. L. REV. 1687, 1693 (2005).

<sup>57</sup> See Lemley & McGowan, *Legal Implications*, *supra* note 44, at 491.

<sup>58</sup> See *supra* note 18 and accompanying text; see also K. Sabeel Rahman, *Regulating Informational Infrastructure: Internet Platforms As the New Public Utilities*, 2 GEO. L. TECH. REV. 234, 241 (2018) (“An information platform is more valuable the more people use it.”); OECD, *Exploring the Economics of Personal Data: A Survey of Methodologies*



platforms are service providers that rely on big-data analytics and machine learning technologies to generate value for their users.<sup>59</sup> As explored below, data analytics and machine learning technologies enable data platforms to optimize, personalize, and continuously diversify their services by identifying patterns in data to predict future trends and remedy unsatisfied user demand.<sup>60</sup> A positive feedback loop that mimics the logic of traditional network effects emerges. The more users utilize these platforms (and the more UGD they surrender in the process), the better and more diversified the platforms’

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for *Measuring Monetary Value*, 220 OECD DIGIT. ECON. PAPERS 2, 34 (2011) [hereinafter OECD, *Exploring Economies*] (“Potential non-linear returns means network effects.”); Erik Brynjolfsson & Andrew McAfee, *The Business of Artificial Intelligence*, HARV. BUS. REV. (July 18, 2017), <https://hbr.org/2017/07/the-business-of-artificial-intelligence> [<https://perma.cc/T29L-PXTJ>] (“The performance of most machine learning systems improves as they’re given more data to work with . . . .”); Charles A. Miller, *Big Data and the Non-Horizontal Merger Guidelines*, 107 CAL. L. REV. 309, 326 (2019) (defining and discussing network effects arising from data); KAI-FU LEE, AI SUPERPOWERS: CHINA, SILICON VALLEY, AND THE NEW WORLD ORDER 19–20 (2018) (“Deep learning’s relationship with data fosters a virtuous circle for strengthening the best products and companies . . . .”); FOSTER PROVOST & TOM FAWCETT, DATA SCIENCE FOR BUSINESS: WHAT YOU NEED TO KNOW ABOUT DATA MINING AND DATA-ANALYTIC THINKING 317 (2013); *The Power of Data Network Effects*, MATT TURCK (Jan. 4, 2016), <https://mattturck.com/the-power-of-data-network-effects> [<https://perma.cc/9WDL-PS84>]; Nick Srnicek, *We Need to Nationalise Google, Facebook and Amazon. Here’s Why*, GUARDIAN (Aug. 30, 2017), <http://www.theguardian.com/commentisfree/2017/aug/30/nationalise-google-facebook-amazon-data-monopoly-platform-public-interest> [<https://perma.cc/J7GP-UDVW>]; Bennett Cyphers & Gennie Gebhart, *Behind the One-Way Mirror: A Deep Dive Into the Technology of Corporate Surveillance*, ELEC. FRONTIER FOUND. (Dec. 2, 2019), <https://www.eff.org/wp/behind-the-one-way-mirror> [<https://perma.cc/5LHR-6QWD>] (“[T]hanks to network effects, the data becomes more valuable when it’s all under one roof.”); Alon Halevy et al., *The Unreasonable Effectiveness of Data*, in 24 IEEE INTELL. SYS. 8, 9 (Brian Brannon ed., 2009) (“[S]imple models and a lot of data trump more elaborate models based on less data.”).

<sup>59</sup> See Marc Bourreau & Alexandre de Streel, Digital Conglomerates and EU Competition Policy 14 (Mar. 11, 2019), [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3350512](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3350512) (“[W]e could adopt a broader definition of a platform as a product or service characterized by strong direct and/or indirect network effects, and not necessarily multi-sided.”).

<sup>60</sup> Machine learning algorithms learn from input data to improve output offerings. See SHAI SHALEV-SHWARTZ & SHAI BEN-DAVID, UNDERSTANDING MACHINE LEARNING: FROM THEORY TO ALGORITHMS 22 (2014); Karen Hao, *What Is Machine Learning?*, MIT TECH. REV. (Nov. 17, 2018), <https://www.technologyreview.com/2018/11/17/103781/what-is-machine-learning-we-drew-you-another-flowchart/> [<https://perma.cc/26TY-YUHN>].

services become.<sup>61</sup> Consequently, the more services data platforms offer and the better the services are, the more users and utilization these platforms attract. Thus, the relationship between utilization and features fuels the positive feedback loop.

UGD can be classified into two types.<sup>62</sup> The first type is the content that users generate and share via social media (e.g., Instagram photos, Facebook commentary, Twitter (now X) tweets, online forums, and product review websites such as Yelp and TripAdvisor).<sup>63</sup> The second type is the personal and behavioral information that users generate and share about themselves, such as demographic and biometric information, clicking patterns, reading history, and dietary habits.<sup>64</sup> Users surrender the second type of UGD in an active and informed manner (e.g., by supplying the information as part of a service's registration process)<sup>65</sup> or in a passive or even subconscious manner (e.g., by scrolling through their Facebook News Feed).<sup>66</sup> Unlike traditional network effects, the nodes in UGD networks represent discrete pieces of UGD rather than individual users' devices. The links that connect the nodes in UGD networks represent the

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<sup>61</sup> See *supra* note 58 and accompanying text.

<sup>62</sup> Cf. Jose Ramon Saura et al., *From User-Generated Data to Data-Driven Innovation: A Research Agenda to Understand User Privacy in Digital Markets*, 60 INT'L J. INFO. MAN. 1, 4 (2021) (distinguishing user-generated content from user-generated behavior).

<sup>63</sup> See *id.* Some of this content is copyright protected. See Uri Y. Hacoheh et al., *A Penny for Their Creation: Appraising Users' Value of Copyrights in Their Social Media Content*, 36 BERKELEY TECH. L.J. 511, 517 (2021).

<sup>64</sup> This definition somewhat parallels the EU's definition of "personal data." See Art. 4 (1) EU General Data Protection Regulation (GDPR): Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 (discussing the protection of natural persons regarding the processing of personal data and on the free movement of such data). See OECD, *Exploring Economies*, *supra* note 58, at 8, for other possible classifications. Some ambiguity exists with respect to smart devices that are partially user-driven but partially autonomous. This Article will consider such data to be UGD.

<sup>65</sup> Even when they do, it is hardly clear that they are aware of the implications of surrendering their UGD. Cf. Hacoheh et al., *supra* note 63, at 519.

<sup>66</sup> Waze made the distinction between passive and active UGD surrender clear in its 2014 "About Us" page: "[U]sers just drive with the app open on their phone to passively contribute traffic and other road data, but they can also take a more active role by sharing road reports on accidents, police traps, or any other hazards along the way, helping to give other users in the area a 'heads-up' about what's to come." *Free Community-Based Mapping, Traffic & Navigation App*, WAZE (Aug. 3, 2014), <https://web.archive.org/web/20140803080158/http://www.waze.com/about> [<https://perma.cc/E642-LVCD>].

insight-gaining correlations among the discrete pieces of UGD, not the communications among the network devices.<sup>67</sup>

UGD network effects are analytically different from traditional network effects. For instance, while Google Search benefits from UGD network effects in many of its features (e.g., identifying searching trends, deciphering relevant results, suggesting popular terms, correcting spelling mistakes in search queries, etc.<sup>68</sup>), Google’s chief economist, Hal Varian, nevertheless correctly asserts, “[t]here are no traditional network effects in Search.”<sup>69</sup> Users do not care whether other people use the same search engine—they

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<sup>67</sup> Much of the value that data platforms generate is based upon finding statistical correlations in UGD. Some critics emphasize that because statistical correlations differ from causal truths, the value generated by UGD-driven analytics is limited, and possibly even misleading. *See, e.g.*, Jesse Frederik & Maurits Martijn, *The New Dot Com Bubble Is Here: It’s Called Online Advertising*, CORRESPONDENT (Nov. 6, 2019), <https://thecorrespondent.com/100/the-new-dot-com-bubble-is-here-its-called-online-advertising/13228924500-22d5fd24> [<https://perma.cc/2SWZ-7QJT>]. Nevertheless, significant statistical correlations in a large enough dataset may reveal invaluable and otherwise inaccessible insights. *See* VIKTOR MAYER-SCHÖNBERGER & KENNETH CUKIER, *BIG DATA: A REVOLUTION THAT WILL TRANSFORM HOW WE LIVE, WORK, AND THINK* 51 (2013). (“[K]nowing *what*, not *why*, is good enough.”); JARON LANIER, *WHO OWNS THE FUTURE* 120 (2014). Moreover, others have argued that the difference between correlation and causation is better viewed as a spectrum rather than a binary, and that with sufficient UGD, we move closer to the causation side. *See* Pedro Domingos, *Ten Myths About Machine Learning*, KDNUGETS, <https://www.kdnuggets.com/ten-myths-about-machine-learning.html> [<https://perma.cc/6T9L-P4F5>] (last visited Sept. 19, 2023); Ron Kohavi & Stefan Thomke, *The Surprising Power of Online Experiments*, HARV. BUS. REV., Sept.–Oct. 2017, <https://hbr.org/2017/09/the-surprising-power-of-online-experiments> [<https://perma.cc/GAQ2-D5H9>]. Lastly, to complicate things further, correlation may transform into causation in the context of UGD-analytics because user preferences are not fixed. *See infra* notes 310–12 and accompanying text; *see also* PEDRO DOMINGOS & MATT RICHARDSON, *MINING THE NETWORK VALUE OF CUSTOMERS*, PROCEEDINGS OF THE SEVENTH INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING 60 (2001); Sylvie Delacroix & Michael Veale, *Smart Technologies and Our Sense of Self: Going Beyond Epistemic Counter-Profiling*, in *LIFE AND THE LAW IN THE ERA OF DATA-DRIVEN AGENCY* 85 (O’Hara & Hildebrandt eds., 2020).

<sup>68</sup> *See infra* notes 86–87, 135–39 and accompanying text.

<sup>69</sup> Varian, *Use and Abuse*, *supra* note 17, at 230. *See also* Varian, *Recent Trends*, *supra* note 17, at 826; Mark A. Lemley, *Antitrust and the Internet Standardization Problem*, 28 CONN. L. REV. 1041, 1052 (1996) (noting “certain Internet application product markets, such as the market for search engines, do not exhibit these [network effects] characteristics,” and erroneously concluding that for this reason such markets “may remain competitive indefinitely”).

only care about how well their search engine performs.<sup>70</sup> For this reason, Varian believes the dynamics defined here as UGD network effects are better explained by the economic concept of “learning by doing.”<sup>71</sup> Learning by doing implies that a firm’s production costs are often reduced as the firm’s production capacity increases.<sup>72</sup>

Yet, UGD network effects do not comfortably fit into the “learning by doing” bracket.<sup>73</sup> Traditionally studied in economic literature, learning by doing is purely a supply-driven phenomenon.<sup>74</sup> Firms learn independently by gaining experience in production. In one case of aircraft manufacturing, Theodore Wright famously stated that labor, material, and overhead requirements decline by around 20% every time cumulative past production doubles.<sup>75</sup> Conversely, in the case of UGD network effects, the supply of UGD—a necessary input for the platform’s learning process—is driven by and dependent on user demands.<sup>76</sup> The more users utilize the platform’s services and the more UGD they serve to the algorithms, the better and more diverse these platforms’ services can become.

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<sup>70</sup> See Varian, *Use and Abuse*, *supra* note 17, at 230.

<sup>71</sup> *Id.*

<sup>72</sup> The concept of “learning by doing” dates back at least to Kenneth Arrow’s seminal 1962 article on the topic. Kenneth J. Arrow, *The Economic Implications of Learning by Doing*, 29 REV. ECON. STUD. 155, 156 (1962).

<sup>73</sup> See Jens Prüfer & Christoph Schottmüller, *Competing with Big Data*, 69 J. INDUS. ECON. 967, 968 (2021) (explaining that UGD network effects are driven both by supply and demand side effects); see also Nathan Newman, *Search, Antitrust, and the Economics of the Control of User Data*, 31 YALE J. ON REG. 401, 421 (2014). Regardless, Varian is correct that UGD is valueless unless refined and put into use by the data platforms. See Varian, *Recent Trends*, *supra* note 17, at 831. Varian is also correct to emphasize that algorithmic innovation can be achieved even without of access to large volumes of UGD. See *id.* at 828.

<sup>74</sup> See Theodore Paul Wright, *Factors Affecting the Cost of Airplanes*, 3 J. AERONAUTICAL SCI. 122, 127–28 (1936); see also C. Lanier Benkard, *Learning and Forgetting: The Dynamics of Aircraft Production*, 90 AM. ECON. REV. 1034, 1034 (2000).

<sup>75</sup> See Arrow, *supra* note 72, at 156.

<sup>76</sup> See Prüfer & Schottmüller, *supra* note 73, at 968 (labeling the phenomenon “data-driven indirect network effects”). Other scholars mix the notions of supply- and demand-side phenomena in different configurations. See Cédric Argenton & Jens Prüfer, *Search Engine Competition With Network Externalities*, 8 J. COMPETITION L. & ECON. 73, 80 (2012) (“[T]he indirect intertemporal externalities we describe can also be viewed as a special version of the learning curve hypothesis.”); IANSITI & LAKHANI, *supra* note 25, at 34 (describing the UGD-driven feedback loop as a mixture of network and learning effects).

Although analytically distinct, UGD and traditional network effects often complement and reinforce one another.<sup>77</sup> A social media platform, such as Facebook, enjoys traditional network effects just like an analog telephone system does—the more users join the platform, the more Facebook’s value to users increases because more users are able to interconnect.<sup>78</sup> Yet unlike its analog counterpart, Facebook also benefits from UGD network effects—the more UGD users generate through messaging, uploading, tagging, liking, sharing, and commenting, the more value Facebook users receive in the form of better and more personalized design, advertising, and content.<sup>79</sup>

Even the mere act of users contacting one another (the essence of Facebook’s traditional network effects) ironically reinforces Facebook’s UGD network effects by improving Facebook’s “People You May Know” recommendation system.<sup>80</sup> Applying these UGD-driven dynamics to a traditional network system would suggest, for

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<sup>77</sup> See Eliana Garcés & Daniel Fanaras, *Antitrust, Privacy, and Digital Platforms’ Use of Big Data: A Brief Overview*, 28 J. ANTITRUST, UNFAIR COMPETITION, & PRIV. L. SECTION CAL. LAWS. ASS’N. 23, 24 (2018) (exploring these synergies); PEDRO DOMINGOS, *THE MASTER ALGORITHM: HOW THE QUEST FOR THE ULTIMATE LEARNING MACHINE WILL REMAKE OUR WORLD* 12 (2015).

<sup>78</sup> To complicate things further, as a multi-sided marketing platform, Facebook also enjoys so-called “indirect” traditional network effects. See *supra* note 44 and accompanying text. As more users join Facebook, the platform becomes more appealing to advertisers as well as application developers and vice versa. See David S. Evans, *The Antitrust Economics of Multi-Sided Platform Markets*, 20 YALE J. ON REG. 325, 331–33 (2003); Lapo Filistrucchi et al., *Identifying Two-Sided Markets*, 36 WORLD COMPETITION 33, 37–39 (2013).

<sup>79</sup> See Nick Statt, *Facebook Is Unleashing Universal Search Across Its Entire Social Network*, VERGE (Oct. 22, 2015, 1:00 PM), <https://www.theverge.com/2015/10/22/9587122/new-facebook-search-all-public-posts> [<https://perma.cc/45DQ-QARJ>] (discussing how UGD improves Facebook search); Catherine Tucker & Alexander Marthews, *Social Networks, Advertising, and Antitrust*, 19 GEO. MASON L. REV. 1211, 1224 (2012) (discussing how UGD improves targeted advertising); Catherine Tucker, *Social Advertising: How Advertising that Explicitly Promotes Social Influence Can Backfire* (June 1, 2016), <https://ssrn.com/abstract=1975897> [<https://perma.cc/2FJP-VL7M>] (discussing how UGD empowers social ads).

<sup>80</sup> But only up to a point. See Sidney Hill, *Is Facebook Too Big for Its Own Good?*, E-COM. TIMES (Sept. 5, 2011, 5:00 AM), <http://www.ecommercetimes.com/story/73216.html?wlc=1315770981> [<https://perma.cc/2ALK-YMHX>] (arguing that Facebook’s scale undermines its function); Bob Briscoe et al., *Metcalfe’s Law Is Wrong*, IEEE SPECTRUM (July 1, 2006), <https://spectrum.ieee.org/metcalfes-law-is-wrong> [<https://perma.cc/8LTQ-4TFU>].

example, that a telephone's archaic design and poor conversation quality would be remodeled and improved as users' telephone conversations became longer and more detailed.<sup>81</sup>

UGD network effect dynamics are multifaceted and complex. The remainder of this Part defines and explores three categories of UGD network effects: optimization, personalization, and diversification.<sup>82</sup> Not all three types apply to every data platform or for every service. Nevertheless, as the following sections show, the various categories of UGD network effects are closely related and often complement one another.

### A. Optimization

Optimization occurs when data platforms collect and analyze UGD to improve their performance.<sup>83</sup> Optimization forms a positive network effect: the more users the platform has, and the more data those users generate, the better the platform's services become.

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<sup>81</sup> See GALLOWAY, *supra* note 2, at 105–06 (“This is tantamount to a car that becomes more valuable with mileage.”); Maurice E. Stucke, *Should We Be Concerned About Dataopolies?*, 2 GEO. L. TECH. REV. 275, 283 (2018) (“The quality of the leading brand’s razors, for example, is not affected when consumers switch from rival razors. In contrast . . . personal digital assistants . . . can improve in quality as more users engage with the digital assistant.”).

<sup>82</sup> Other commentators defining UGD-driven effects typically follow the common economic distinction between scale (or volume) and scope (or variety) of data. See STUCKE & GRUNES, *supra* note 18, at 170; DATA-DRIVEN INNOVATION, *supra* note 16, at 10. Roughly speaking, optimization usually refers to scale-driven effects, whereas personalization refers to scope-driven effects. Diversification involves both scale and scope of data effects. Nevertheless, this analogy is not perfect. For example, while some optimization practices involve only scale of data effects (e.g., utilizing location data to improve navigation systems), other optimization practices also involve scope effects (e.g., running a multi-variable A/B test to improve the visualization of a Facebook webpage). Personalization practices also involve both scale and scope effects. See *infra* note 144–46 and accompanying text.

<sup>83</sup> See Howard A. Shelanski, *Information, Innovation, and Competition Policy for the Internet*, 161 U. PENN. L. REV. 1663, 1680 (2013); Roisin Comerford & D. Daniel Sokol, *Does Antitrust Have a Role to Play in Regulating Big Data?*, in CAMBRIDGE HANDBOOK OF ANTITRUST, INTELLECTUAL PROPERTY, AND HIGH TECH 293–316 (Roger D. Blair & D. Daniel Sokol eds., 2017); DIG. COMPETITION, *supra* note 18, at 23; see also STUCKE & GRUNES, *supra* note 18, at 170; DATA-DRIVEN INNOVATION, *supra* note 16, at 29.

Data platforms can use UGD in three main ways to optimize services: scaling, modeling, and testing.<sup>84</sup> First, the vast scale of UGD optimizes some of the data platforms' services by making them more authoritative, engaging, or valuable to users.<sup>85</sup> For instance, the more people use the Google search engine to search the web, the more authoritative Google Trends (a feature that enables users to evaluate their search queries' popularity worldwide in real time) becomes.<sup>86</sup> In 2014, Google Trends was already authoritative enough to upset an almost century-old tradition of the *Time* magazine editors independently deciding who should be nominated as "Person of the Year."<sup>87</sup> Amazon also relies on UGD-driven scaling effects to provide trustworthy star ratings for products, which reinforces Amazon's authority as a "go-to place" for product recommendations.<sup>88</sup> In 2018, confident in its rich corpus of user-generated ratings as a

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<sup>84</sup> This categorization is not exhaustive, and some practices may fit more than one category.

<sup>85</sup> See James Currier, *What Makes Data Valuable: The Truth About Data Network Effects*, NFX (Feb. 2020), <https://www.nfx.com/post/truth-about-data-network-effects> [<https://perma.cc/62E7-JE9D>] (describing how a "data scale advantage" is the next best thing from a real network effect because it creates both a comprehensive product database and a unique value for customers).

<sup>86</sup> See Simon Rogers, *What Is Google Trends Data—and What Does It Mean?*, GOOGLE NEWS LAB (July 1, 2016), <https://medium.com/google-news-lab/what-is-google-trends-data-and-what-does-it-mean-b48f07342ee8> [<https://perma.cc/NJ59-CSH8>] ("Trends data can provide a powerful lens into what Google users are curious about and how people around the world react to important events.").

<sup>87</sup> See Sam Frizell, *These Are the Most Searched Candidates on the Person of the Year Poll*, TIME (Dec. 5, 2014), <https://time.com/time-person-of-the-year-google/> [<https://perma.cc/6CUB-CSF8>].

<sup>88</sup> See Louise Matsakis, *What Do Amazon's Star Ratings Really Mean?*, WIRED (May 25, 2019), <https://www.wired.com/story/amazon-stars-ratings-calculated/> [<https://perma.cc/59WG-TRJK>] ("Higher scores are crowdsourced seals of approval."); Lina M. Khan, *Amazon's Antitrust Paradox*, 126 YALE L.J. 710, 785 (2017) ("Amazon's user reviews, for example, serve as a form of network effect: the more users that have purchased and reviewed items on the platform, the more useful information other users can glean from the site."). Amazon star-rating enjoys more than simple scaling effects, as it also incorporates machine learning optimization. See Ben Fox Rubin, *Amazon Looks to Improve Customer-Reviews System with Machine Learning*, CNET (June 19, 2015), <https://www.cnet.com/tech/services-and-software/amazon-updates-customer-reviews-with-new-machine-learning-platform/> [<https://perma.cc/E36H-J4M8>].

valuable signal of product quality, Amazon launched “4-star,”<sup>89</sup> “a new physical store where everything for sale is rated four stars and above, is a top seller, or is new and trending on Amazon.com.”<sup>90</sup> Social networking sites (such as Facebook and Instagram) also rely on UGD to keep their platform engaging.<sup>91</sup> Finally, websites for crowd-sourced information (such as Wikipedia and Quora) or reviews (such as Yelp, TripAdvisor, and Zagat) require large volumes of UGD to remain valuable and relevant.<sup>92</sup>

Second, optimization occurs when data platforms feed UGD into machine learning models to improve their services’ performance.<sup>93</sup> Google uses UGD from clicks to decipher the likeliest meaning of opaque queries (e.g., “cheap apple”) and to provide accurate search results (e.g., “cheap iPhone” vs. “cheap fruits”).<sup>94</sup> As Google’s former chief of search quality, Udi Manber, testified to the FTC, “[t]he ranking itself is affected by the click data. If we discover that for a particular query, hypothetically, 80% of people click on result No.

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<sup>89</sup> *Introducing Amazon 4-star*, ABOUT AMAZON (Sept. 26, 2018), <https://www.aboutamazon.com/news/retail/introducing-amazon-4-star> [<https://perma.cc/FQ25-S2ZG>].

<sup>90</sup> *Id.*

<sup>91</sup> See Hacothen et al., *supra* note 63.

<sup>92</sup> See Daniel L. Rubinfeld & Michal S. Gal, *Access Barriers to Big Data*, 59 ARIZ. L. REV. 339, 355–56 (2017) [hereinafter Rubinfeld & Gal, *Access Barriers*] (“[T]he more data about the quality of hotels based on reviews from past users can be found on TripAdvisor, the more valuable the data-based information to each user.”). Unsurprisingly, these websites incentivize users to submit content. See ANDRES V. LERNER, *THE ROLE OF ‘BIG DATA’ IN ONLINE PLATFORM COMPETITION* 25 (2014), [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2482780](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2482780) [<https://perma.cc/W9SX-FKFZ>] (explaining how TripAdvisor and Amazon offer incentives to users to write reviews).

<sup>93</sup> See *supra* note 60 and accompanying text.

<sup>94</sup> See Argenton & Prüfer, *supra* note 76, at 76 (“Our key insight is that the production of search quality is characterized by a peculiar (intertemporal) type of indirect network externalities.”); STUCKE & GRUNES, *supra* note 18, at 170; JOHN BATTLE, *THE SEARCH: HOW GOOGLE AND ITS RIVALS REWROTE THE RULES OF BUSINESS AND TRANSFORMED OUR CULTURE* 6 (Portfolio 2006). The importance of query log data for search engine quality has also been acknowledged in computer science literature. See Amanda Spink et al., *Searching the Web: The Public and Their Queries*, 52 J. AM. SOC’Y INFO. SCI. & TECH. 226, 226 (2001); Fabrizio Silvestri, *Mining Query Logs: Turning Search Usage Data into Knowledge*, 4 FOUND. & TRENDS INFO. RETRIEVAL 1, 3 (2010); Steven Levy, *Secret of Googlenomics: Data-Fueled Recipe Brews Profitability*, WIRED (June 17, 2009), [http://www.wired.com/culture/culturereviews/magazine/17-06/nep\\_googlenomics](http://www.wired.com/culture/culturereviews/magazine/17-06/nep_googlenomics) [<https://perma.cc/9D5A-SJRT>].



2 and only 10% click on result No. 1, after a while, we figure out, well, probably result No. 2 is the one people want. So, we'll switch it."<sup>95</sup>

Similarly, Google uses UGD from typing (e.g., grammar, spacing, and typos) and query data (e.g., choice and frequency of words or sentences) to improve its spellcheck and autocomplete functions.<sup>96</sup> Navigation systems, such as Waze, use location data to improve their mapping, course-plotting, and real-time notification services.<sup>97</sup> Digital assistance services, such as Amazon's Alexa, Apple's Siri, and Microsoft's Cortana, utilize conversation data to improve their functionality.<sup>98</sup> Video streaming services, such as Netflix and Amazon Prime, rely on UGD from views to inform their entertainment portfolios.<sup>99</sup> Similar examples are abundant.

The third and final form of service optimization occurs through UGD-driven experimentation of new features, functions, and visualizations.<sup>100</sup> One standard method in this category is called A/B

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<sup>95</sup> FED. TRADE COMM'N BUREAU OF COMPETITION, REPORT RE GOOGLE INC. 14 (Aug. 8, 2012), <http://graphics.wsj.com/google-ftc-report/> [<https://perma.cc/Q9N4-G2C7>]. See also SUBCOMM., INVESTIGATION OF COMPETITION, *supra* note 18, at 64 (“[C]lick-and-query data is used to refine the search algorithm and the relevance of search results.”); STUCKE & GRUNES, *supra* note 18, at 170; Argenton & Prüfer, *supra* note 76, at 74–75; cf. MARTIN MOORE & DAMIAN TAMBINI, DIGITAL DOMINANCE: THE POWER OF GOOGLE, AMAZON, FACEBOOK, AND APPLE 35 (Oxford Univ. Press 2018); Comerford & Sokol, *supra* note 83, at 4; Hemphill, *supra* note 29, at 1980; LERNER, *supra* note 92, at 11.

<sup>96</sup> See Ann Smarty, *Google Spell Check and How it Works*, INTERNET MKTG. NINJAS BLOG (June 17, 2013), <https://www.internetmarketingninjas.com/blog/search-engine-optimization/google-spell-check/> [<https://perma.cc/R8CS-B3WN>] (noting that Google spell checker “is all user-behavior based”); Omer Tene, *What Google Knows: Privacy and Internet Search Engines*, 4 UTAH L. REV. 1433, 1451 (2008).

<sup>97</sup> See STUCKE & GRUNES, *supra* note 18, at 171–73.

<sup>98</sup> See Christopher Mims, *Ask M for Help: Facebook Tests New Digital Assistant*, WALL ST. J. (Nov. 9, 2015), <https://www.wsj.com/articles/ask-m-for-help-facebook-tests-new-digital-assistant-1447045202> [<https://perma.cc/DS6S-V753>].

<sup>99</sup> See STUCKE & GRUNES, *supra* note 18, at 183 (“[I]n tracking its subscribers’ viewing habits [Netflix] can predict other movies and shows that the subscriber may enjoy.”); David Carr, *Giving Viewers What They Want*, N.Y. TIMES (Feb. 24, 2013), <https://www.nytimes.com/2013/02/25/business/media/for-house-of-cards-using-big-data-to-guarantee-its-popularity.html> [<https://perma.cc/4556-E78Y>] (describing how big data analytics predicted the success and rationalized the spending on the hit show *House of Cards*).

<sup>100</sup> See CRÉMER ET AL., *supra* note 18, at 35 (“[In the digital sphere,] products are in constant evolution, permanently being reworked.”); Steve Lohr, *With the Bing Search*

testing, whereby users are presented with a new feature or a feature change (e.g., a change in interface design or functionality), and their reaction to the stimuli is registered, monitored, and compared to those of other users.<sup>101</sup> If the tested feature improves the service's performance by, for example, increasing user engagement through more clicks, extended visits, and more purchases, the new feature will be adopted.<sup>102</sup> If the tested feature does not improve the service's performance, the data platforms will phase that feature out (often without users even noticing).<sup>103</sup> Data platforms describe A/B testing as a highly effective way to improve their services' performance; in Netflix's experience, for example, using A/B tests to optimize image choice associated with movie titles increased viewing records by 20–30%.<sup>104</sup>

Given such positive results, it is unsurprising that the use of A/B testing is rapidly expanding.<sup>105</sup> For example, in 2000, Google started with a single A/B test to optimize the number of results it displayed

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*Engine, Microsoft Plays the Underdog*, N.Y. TIMES (July 30, 2011), <https://www.nytimes.com/2011/07/31/technology/with-the-bing-search-engine-microsoft-plays-the-underdog.htm> [<https://perma.cc/8TN8-DMZJ>]. *But cf.* LERNER, *supra* note 92, at 33 (“[Many innovative features] are driven primarily by engineering talent, not a large scale of user data.”).

<sup>101</sup> See Todd Haugh et al., *The Code of the Platform*, 54 GA. L. REV. 605, 622 (2020) (“Platform companies . . . employ teams of behavioral, social, and data scientists to experiment on users and design interfaces to maximize transactions and profitability.”); *see also* Kohavi & Thomke, *supra* note 67.

<sup>102</sup> See discussion *infra* Section III.B, for the problematic nature of these matrices.

<sup>103</sup> See Brian Christian, *The A/B Test: Inside the Technology That's Changing the Rules of Business*, WIRED (Apr. 25, 2012), <https://www.wired.com/2012/04/ff-abtesting/> [<https://perma.cc/B6HT-8LY4>].

<sup>104</sup> See Janko Roettgers, *This Simple Trick Helped Netflix Increase Video Viewing by More Than 20 Percent*, VARIETY (Jan. 7, 2016), <https://variety.com/2016/digital/news/netflix-ab-tests-image-optimization-trick-1201674325/> [<https://perma.cc/KVS6-LZ9P>]; Steve Urban et al., *It's All A/Bout Testing*, NETFLIX TECH. BLOG (Apr. 29, 2021), <https://netflixtechblog.com/its-all-a-bout-testing-the-netflix-experimentation-platform-4e1ca458c15> [<https://perma.cc/5Q82-LU92>].

<sup>105</sup> Moreover, A/B-type testing may incorporate multiple variables to substantially improve their performance. See Neil Patel, *A/B Testing vs Multiple Variant Testing: And the Winner Is . . . ?*, NEIL PATEL, <https://neilpatel.com/blog/ab-testing-vs-multiple-variant/> [<https://perma.cc/64KC-2JDL>] (last visited Oct. 16, 2023) (“According to Optimizely, just 14% of A/B tests significantly improve conversion rates. On the other hand, tests with 4 variants improve conversion rates 27% of the time.”).

on each web page; by 2011, it used more than 7,000 A/B tests.<sup>106</sup> A Netflix executive similarly boasted, “every product change Netflix considers goes through a rigorous A/B testing process before becoming the default user experience.”<sup>107</sup>

Of course, not all optimization feedback loops are sustainable, and some will experience diminishing returns to scale over time.<sup>108</sup> Consider the marginal value of product reviews on Amazon.com; after a limited number of helpful product reviews for a clothing hanger, the value of each additional clothing hanger review is likely to be almost negligible for the average user.<sup>109</sup> If the returns to scale in UGD diminish, the positive feedback loop resulting from that repeated use also dissolves.

Nevertheless, in many cases there are reasons returns to scale in UGD will not diminish quickly.<sup>110</sup> First, there are situations where near-infinite scale is valuable. In these cases, even if the returns to scale of UGD diminish at some point, as the computer scientist

<sup>106</sup> See Christian, *supra* note 103.

<sup>107</sup> Urban et al., *supra* note 104.

<sup>108</sup> See Inge Graef, *Market Definition and Market Power in Data: The Case of Online Platforms*, 38 WORLD COMPETITION 473, 486 (2015), <https://kluwerlawonline.com/journalarticle/World+Competition/38.4/WOCO2015040> [<https://perma.cc/FBF7-XWSH>] (“However, the benefits relating to the availability of data for the provision of services on the user as well as the advertiser side are subject to diminishing returns to scale.”); Michal Kosinski et al., *Private Traits and Attributes Are Predictable from Digital Records of Human Behavior*, 110 PROC. NAT’L ACAD. SCI. 5802, 5804 (2013) (“Knowing further Likes increases the accuracy but with diminishing returns from each additional piece of information.”); see also Kelvin Yu, *No, AI Does Not Lead to Monopoly Markets*, MEDIUM (July 26, 2019), <https://medium.com/profiles-in-entrepreneurship/no-ai-does-not-lead-to-monopoly-markets-7368ac4f536b> [<https://perma.cc/ZZ8Y-FMCC>]; Martin Casado & Peter Lauten, *The Empty Promise of Data Moats*, ANDREESSEN HOROWITZ (May 9, 2019), <https://a16z.com/2019/05/09/data-network-effects-moats/> [<https://perma.cc/24YD-URQJ>]; Tejas N. Narechania, *Machine Learning as Natural Monopoly*, 107 IOWA L. REV. 1543, 1582 (2022).

<sup>109</sup> See, e.g., Neil Davey, *How Many Online Reviews Are Needed to Optimise Sales—and What’s the Best Rating?*, MYCUSTOMER (June 22, 2017), <https://www.mycustomer.com/selling/ecommerce/how-many-online-reviews-are-needed-to-optimise-sales-and-whats-the-best-rating> [<https://perma.cc/8WQ7-PA8R>] (noting that products’ reviews showed “diminishing returns reported after 50 reviews”).

<sup>110</sup> See *The Data Freedom Act*, RADICALXCHANGE, <https://www.radicalxchange.org/media/papers/data-freedom-act.pdf> [<https://perma.cc/T7RE-MB38>] (“Data—especially data about people—has aspects of both increasing and decreasing returns that cannot be easily teased apart.”).

Pedro Domingos wrote in *The Master Algorithm*, “that saturation point is nowhere in sight.”<sup>111</sup> For example, although the incremental value of an Amazon review for a popular product is likely to diminish quickly (say somewhere after thirty-four to fifty reviews),<sup>112</sup> Amazon still has a nearly infinite selection of less popular unrated products. In fact, over a third of Amazon’s total sales often come from these “long-tail” niche products that are unavailable in brick-and-mortar stores.<sup>113</sup> For long-tail products with zero ratings, research suggests that even a single user-generated review may boost user traffic by 108% and the user conversion rate by 65%.<sup>114</sup> Similarly, consider Google Search. While the increasing returns of UGD from clicks (in the form of better-ranked search results) taper off quickly for any given query,<sup>115</sup> the possible queries are infinite. Based on Google, roughly 840 million daily queries are entirely new.<sup>116</sup> Like Amazon’s inventory, the UGD-driven value for these “long-tail” queries does not fully diminish.<sup>117</sup>

Whenever users place a high value on infinite scale, the rate of return for UGD is unlikely to diminish quickly.<sup>118</sup> More importantly,

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<sup>111</sup> DOMINGOS, *supra* note 77, at 12.

<sup>112</sup> See Davey, *supra* note 109.

<sup>113</sup> See BRYNJOLFSSON ET AL., THE LONGER TAIL: THE CHANGING SHAPE OF AMAZON’S SALES DISTRIBUTION CURVE 1 (2010), <https://ssrn.com/abstract=1679991> [<https://perma.cc/2NHJ-RNCP>] (“Our analyses suggest that by 2008, niche books account for 36.7% of Amazon’s sales.”); see also Chris Anderson, *The Long Tail*, WIRED (Oct. 1, 2004) <https://www.wired.com/2004/10/tail/> [<https://perma.cc/X2N7-KX5J>].

<sup>114</sup> See Davey, *supra* note 109.

<sup>115</sup> See STUCKE & GRUNES, *supra* note 18, at 178–79.

<sup>116</sup> See Barry Schwartz, *Google Reaffirms 15% of Searches Are New, Never Been Searched Before*, SEARCH ENGINE LAND (Apr. 25, 2017), <https://searchengineland.com/google-reaffirms-15-searches-new-never-searched-273786> [<https://perma.cc/8F2V-M674>] (noting Google processes 15% new queries per day); *How Many Google Searches Per Day? SEM Pros Should Know This!*, SKAI (Feb. 25, 2019), <https://skai.io/monday-morning-metrics-daily-searches-on-google-and-other-google-facts/> [<https://perma.cc/6C4Z-NGVA>].

<sup>117</sup> See AGRAWAL ET AL., PREDICTION MACHINES: THE SIMPLE ECONOMICS OF ARTIFICIAL INTELLIGENCE 52–53 (2018) (noting that, even if value is diminishing in the statistical sense, in the economic sense, so long as there is a long tail, users will always tip in favor of the best product—meaning that, economically speaking, the returns are increasing); see also *supra* note 93 and accompanying text.

<sup>118</sup> See Martin Casado & Matt Bornstein, *The New Business of AI (and How It’s Different From Traditional Software)*, FUTURE (Feb. 16, 2020), <https://future.com/new-business-ai-different-traditional-software/> [<https://perma.cc/XEA8-3JHX>] (“AI lives in the long

even if users place a relatively low value on infinite scale, even a marginal benefit may be sufficient to create a positive feedback loop in a competitive setting.<sup>119</sup> Like the famous joke about outrunning a bear,<sup>120</sup> Google does not have to outperform Bing in every search query; it only needs to be as good as Bing for most queries and slightly better than Bing on occasion.<sup>121</sup> This is sufficient in the race to keep users choosing Google.

Second, other types of UGD are unlikely to experience diminishing returns because of temporal significance. For example, health and financial UGD used for longitudinal measurements will continue to hold value over time because they allow data platforms to track and predict rare “black swan” events.<sup>122</sup> The returns of user location data are also unlikely to diminish for services such as Waze, which need to be updated in real-time to provide up-to-date driving

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tail . . . .”); David Lehr & Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. DAVIS L. REV. 654, 687 (2017) (“Often, machine learning is applied to predict exactly these kinds of rare events.”); Anand Rajaraman, *More Data Usually Beats Better Algorithms*, DATAWOCKY (Mar. 24, 2008), <https://anand.typepad.com/datawocky/2008/03/more-data-usual.html> [<https://perma.cc/54VX-N84Q>] (“[T]he bigger point is, adding more, independent data usually beats out designing ever-better algorithms to analyze an existing data set.”).

<sup>119</sup> See AGRAWAL ET AL., *supra* note 117, at 53 (“[F]rom a business viewpoint, data might be most valuable if you have more and better data than your competitor.”); STIGLER FINAL REPORT, *supra* note 18, at 50; Iain M. Cockburn et al., *The Impact of Artificial Intelligence on Innovation* 4 (Nat’l Bureau of Econ. Rsch., Working Paper No. 24449, 2018), [https://www.nber.org/system/files/working\\_papers/w24449/w24449.pdf](https://www.nber.org/system/files/working_papers/w24449/w24449.pdf) [<https://perma.cc/5Z3W-4K4Z>].

<sup>120</sup> One version of this joke was told by Benedict Cumberbatch (as Alan Turing) in the film *The Imitation Game*: “There are two people in a wood, and they run into a bear. The first person gets down on his knees to pray; the second person starts lacing up his boots. The first person asks the second person, ‘My dear friend, what are you doing? You can’t outrun a bear.’ To which the second person responds, ‘I don’t have to. I only have to outrun you.’” See Collin Brooke, *Outrunning the Bear*, MEDIUM (May 26, 2016), <https://cgbrooke.medium.com/outrunning-the-bear-9608a58238f0> [<https://perma.cc/G9F5-QUEW>]; THE IMITATION GAME (Lionsgate 2014).

<sup>121</sup> See AGRAWAL ET AL., *supra* note 117, at 53 (“Being even a little better in search can lead to a big difference in market share and revenue.”).

<sup>122</sup> See IAN OPPERMAN ET AL., DATA SHARING FRAMEWORKS: TECHNICAL WHITE PAPER, 26 (2017); see also NASSIM TALEB, THE BLACK SWAN: THE IMPACT OF THE HIGHLY IMPROBABLE (Random House 2007) (popularizing the concept of “Black Swan” events).

estimations and time-sensitive notifications about accidents, road maintenance, and other hazards.<sup>123</sup>

Finally, UGD-driven experimentation does not suffer decreasing returns.<sup>124</sup> As Pedro Domingos notes:

Every feature of a product, every corner of a website can potentially be improved using machine learning. Should the link at the bottom of the page be red or blue? Try them both and see which one gets the most clicks. Better still, keep the learners running and continuously adjust all aspects of the website.<sup>125</sup>

In other words, because real-time experimentation is effectively unbounded, it is challenging to talk about UGD's diminishing returns to scale in this context.

### B. Personalization

Personalization occurs when data platforms collect and analyze UGD to profile, segment, and then better tailor their services to specific individual user preferences.<sup>126</sup> Personalization extends and

<sup>123</sup> See James Currier, *What Makes Data Valuable: The Truth About Data Network Effects*, NFX (Feb. 2020), <https://www.nfx.com/post/truth-about-data-network-effects> [<https://perma.cc/MCB7-HL9K>] (“The *corpus* of data ages so quickly that it doesn’t have time to hit the point of diminishing returns—new data is always valuable.”); Matsakis, *supra* note 88 (“Five-star ratings from three years ago probably shouldn’t count as much as three-star ratings left just last week.”); Hemphill, *supra* note 29, at 1979 (“The importance of user history varies by application, and more recent user data often have an outsized importance.”).

<sup>124</sup> See WENDY LI ET AL., VALUE OF DATA: THERE’S NO SUCH THING AS A FREE LUNCH IN THE DIGITAL ECONOMY 29 (RIETI Discussion Paper Series No. 19-E-022, 2019), <https://www.rieti.go.jp/jp/publications/dp/19e022.pdf> [<https://perma.cc/JVB5-7BRN>] (“[A]n extension of data to multiple dimensions may not suffer decreasing returns.”).

<sup>125</sup> DOMINGOS, *supra* note 77, at 13.

<sup>126</sup> See ANNABELLE GAWER, COMPETITION POLICY AND REGULATORY REFORMS FOR BIG DATA: PROPOSITIONS TO HARNESS THE POWER OF BIG DATA WHILE CURBING PLATFORMS’ ABUSE OF DOMINANCE 11 (2016) (“Data can be assembled about an individual, over time, revealing patterns of behavior.”) (note submitted as background material to the 126<sup>th</sup> meeting of the OECD Competition Committee); LEE, *supra* note 58, at 107 (“Internet AI is largely about using AI algorithms as *recommendation engines*: systems that learn our personal preferences and then serve up content hand-picked for us.”); Frederik J. Zuiderveen Borgesius et al., *Should We Worry about Filter Bubbles?*, INTERNET POL’Y REV. (Mar. 31, 2016), <https://policyreview.info/articles/analysis/should-we-worry-about-filter-bubbles> [<https://perma.cc/NF7P-UFAP>] (“[P]ersonalisation is described as the

reinforces the positive network effect discussed so far: the richer and more diverse the data that users generate and contribute to data platforms, the better these platforms become at profiling user preferences and personalizing their services to those preferences.<sup>127</sup> The more personalized the platforms' services become, the likelier users are to utilize them and thereby generate even more data that would further enable data platforms to personalize their services.<sup>128</sup>

In machine learning lexicon, personalization algorithms are often termed “recommendation systems.”<sup>129</sup> These systems are good at inferring user preferences and demands based on the data that they generate (a content-based filtering approach)<sup>130</sup> or the data generated by other, similarly situated users (a collaboration-based

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phenomenon that media content is not the same for every user, but tailored to different groups or individuals.”); LERNER, *supra* note 92, at 12.

<sup>127</sup> See CRÉMER ET AL., *supra* note 18, at 28 (explaining the importance of individual-level data increases); STIGLER FINAL REPORT, *supra* note 18, at 46–47.

<sup>128</sup> See Niko Pajkovic, *Algorithms and Taste-Making: Exposing the Netflix Recommender System's Operational Logics*, 28 CONVERGENCE 214, 225 (2021) (“[A] more personalized experience, as well as more accurate recommendations, should then lead to greater user consumption and interaction, and therefore more data, better recommendations, and so on and so forth.”); Julia Alexander, *TikTok Reveals Some of the Secrets, and Blind Spots, of Its Recommendation Algorithm*, VERGE (June 18, 2020), <https://www.theverge.com/2020/6/18/21296044/tiktok-for-you-page-algorithm-sides-engagement-data-creators-trends-sounds> [<https://perma.cc/H9X8-4MQH>] (“TikTok is often applauded for its recommendation system.”).

<sup>129</sup> See Christoph B. Graber, *The Future of Online Content Personalisation: Technology, Law and Digital Freedoms* 6 (Univ. Zurich, Working Paper, No. 2016/01, 2016) (“Personalisation technologies essentially work as recommenders.”); Catalina Goanta & Jerry Spanakis, *Influencers and Social Media Recommender Systems Unfair Commercial Practices in EU and US Law* 8 (Stanford-Vienna Transatlantic Tech. L.F., Working Paper No. 54, 2020), <https://law.stanford.edu/publications/no-54-influencers-and-social-media-recommender-systems-unfair-commercial-practices-in-eu-and-us-law/> [<https://perma.cc/FD7Z-P62W>].

<sup>130</sup> A common example of a content-based system is the “radio” function that exists in many music-streaming services. Once a user listens to music of a specific genre/musician, the services automatically suggest similar music. See, e.g., Houtao Deng, *Recommender Systems in Practice*, TOWARD DATA SCI. (Feb. 13, 2019), <https://towardsdatascience.com/recommender-systems-in-practice-cef9033bb23a> [<https://perma.cc/3M3K-38V9>]; Pasquale Lops et al., *Content-Based Recommender Systems: State of the Art and Trends*, in RECOMMENDER SYSTEMS HANDBOOK 74 (2011) (noting that content-based recommender systems try to recommend items similar to those a given user has liked in the past); Graber, *supra* note 129.

filtering approach).<sup>131</sup> For example, Netflix may recommend *The Dark Knight* to Joe because Joe liked *Batman Begins*, or because Joe liked *The Social Dilemma* and other users who liked *The Social Dilemma* also enjoyed *The Dark Knight*.<sup>132</sup> Over time, recommender systems have grown in complexity, and today many systems employ an extensive mixture of traditional content-based and collaborative filtering approaches, as well as newer approaches.<sup>133</sup>

Most services in the digital UGD-driven economy—streaming services, e-commerce websites, social media platforms, and even search engines—use machine learning algorithms to personalize their offerings.<sup>134</sup> Google’s search engine, for example, does not

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<sup>131</sup> See Lops et al., *supra* note 130 (“[C]ollaborative recommendation paradigms identify users whose preferences are similar to those of the given user and recommend items they have liked.”); Graber, *supra* note 129.

<sup>132</sup> See Pajkovic, *supra* note 128, at 217. A content-based recommender logic is evident in Netflix’s Video Similarity Ranker (e.g., “because you watched”). See David Chong, *Deep Dive into Netflix’s Recommender System*, TOWARDS DATA SCI. (Apr. 30, 2020), <https://towardsdatascience.com/deep-dive-into-netflixs-recommender-system-341806ae3b48> [<https://perma.cc/33CN-B3BA>]. Conversely, a collaborative-filtering logic is evident in what Netflix calls “taste communities,” which form the basis of Netflix’s recommender system. See Libby Plummer, *This Is How Netflix’s Top-Secret Recommendation System Works*, WIRED (Aug. 22, 2017), <https://www.wired.co.uk/article/how-do-netflixs-algorithms-work-machine-learning-helps-to-predict-what-viewers-will-like> [<https://perma.cc/9JHD-AAU8>]; see also THE DARK KNIGHT (Warner Bros. 2008); BATMAN BEGINS (Warner Bros. 2005); THE SOCIAL DILEMMA (Netflix 2020).

<sup>133</sup> See, e.g., Carlos A. Gomez-Uribe & Neil Hunt, *The Netflix Recommender System: Algorithms, Business Value, and Innovation*, 6 ASS’N COMPUTING MACH. TRANSACTIONS MGMT. INF. SYS., no. 13, 2015, at 1–9; Goanta & Spanakis, *supra* note 129, at 8.

<sup>134</sup> Personalization systems are most controversial in search engines. Cf. Barry Smyth et al., *Communities, Collaboration, and Recommender Systems in Personalized Web Search*, in RECOMMENDER SYS. HANDBOOK 579, 584 (Ricci et al. eds., 2011); Tobias D. Krafft et al., *What Did You See? A Study to Measure Personalization in Google’s Search Engine*, 38 EPJ DATA SCI. 1, 1 (2019); Nick Statt, *Google Personalizes Search Results Even When You’re Logged Out, New Study Claims*, VERGE (Dec. 4, 2018), <https://www.theverge.com/2018/12/4/18124718/google-search-results-personalized-unique-duckduckgo-filter-bubble> [<https://perma.cc/HPN7-ESXW>]; Frank Pasquale, *Paradoxes of Digital Antitrust: Why the FTC Failed to Explain Its Inaction on Search Bias*, HARV. J.L. & TECH. OCCASIONAL PAPER SERIES 8 (July 2013), <https://jolt.law.harvard.edu/assets/misc/Pasquale.pdf> [<https://perma.cc/2HU9-S9F7>] (“Search is as much about personalized service as it is about technical principles of information organization and retrieval.”); Florian Wagner-Von Papp, *Should Google’s Secret Sauce be Organic?*, 16 MELBOURNE J. INT’L L. 1, 29 (2015) (“[M]ost search engines, except for DuckDuckGo, learn about user intent not only from other search users’ searches,



only aggregate users' clicking, typing, and query data to optimize its ranking, spellchecking, and autocompleting functionalities,<sup>135</sup> it also uses the same and other data<sup>136</sup> to construct detailed user profiles and personalize their already-optimized offerings accordingly.<sup>137</sup> In this way, Google's search engine can decipher whether generic terms such as "football" should be interpreted as "soccer" (for an Italian user) or as "gridiron" (for an American user).<sup>138</sup> Similarly, it can direct users looking generically for "pizza" to either "Domino's Pizza" or "Pizza Hut," depending on their past browsing activity or geographic location.<sup>139</sup>

As for Netflix's streaming service, many are familiar with its title recommendations ("recommended for Joe"), predictions ("97% match for Joe"), and notifications ("a new release for Joe"), but these only scratch the surface of Netflix's personalization ecosystems.<sup>140</sup> As Niko Pajkovic explains:

Today, each user's entire experience of the Netflix homepage is algorithmically generated, including all suggested titles, the ranking of those titles within

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but also from the individual user's previous searches."). *But see* Jillian D'Onfro, *We Sat in on an Internal Google Meeting Where They Talked About Changing the Search Algorithm—Here's What We Learned*, CNBC (Sept. 18, 2018), <https://www.cnbc.com/2018/09/17/google-tests-changes-to-its-search-algorithm-how-search-works.html> [<https://perma.cc/RQF2-UJDM>] ("Right now, there is very little search personalization.").

<sup>135</sup> Including, for example, the users' IP addresses, locations, browsing behaviors, or operating system information. *See supra* notes 93–98 and accompanying text.

<sup>136</sup> *See* JOHN CHENEY-LIPPOLD, *WE ARE DATA: ALGORITHMS AND THE MAKING OF OUR DIGITAL SELVES* 13 (2017).

<sup>137</sup> *See* Statt, *supra* note 134.

<sup>138</sup> *See* Eli Schwartz, *Here's How Google Decides the Language of Your Results*, LINKEDIN (Aug. 8, 2014), <https://www.linkedin.com/pulse/20140808070327-7287475-here-s-how-google-decides-the-language-of-your-results/> [<https://perma.cc/QA6D-QF7H>].

<sup>139</sup> *See* Aleh Barysevich, *5 Ways to Optimize for Personalized Search*, SEARCH ENGINE J. (Aug. 2, 2018), <https://www.searchenginejournal.com/5-ways-to-optimize-for-personalized-search/263499/> [<https://perma.cc/PQB6-C749>].

<sup>140</sup> In the words of Netflix, their "deep personalization" has enabled the company to "not have just one Netflix product but hundreds of millions of products: one for each member profile." Pajkovic, *supra* note 128, at 218. *See also* Springboard India, *How Netflix's Recommendation Engine Works?*, MEDIUM (Nov. 5, 2019), [https://medium.com/@springboard\\_ind/how-netflixs-recommendation-engine-works-bd1ee381bf81](https://medium.com/@springboard_ind/how-netflixs-recommendation-engine-works-bd1ee381bf81) [<https://perma.cc/4JP3-9JMM>].

custom ‘rows’ (e.g., ‘Crime Dramas,’ ‘Top Picks,’ etc.) and the ordering of those rows on the homepage . . . . Furthermore, almost all the information displayed regarding a specific title is personalized, including its match score, artwork, trailer, synopsis, and metadata (e.g., awards, cast, etc.).<sup>141</sup>

Netflix also uses personalization in its search service. When users search its catalog, Netflix automatically ranks its results based on an algorithmic prediction of each user’s interests.<sup>142</sup> Accordingly, when a user looks for a title missing from Netflix’s inventory, the search engine generates a recommendation from available titles that the algorithms consider the most similar to the title the user sought.<sup>143</sup>

Unlike the optimization techniques discussed above, which reflect user preferences as a unified group, personalization techniques require a much deeper and more nuanced understanding of individuals. For that reason, recommendation algorithms can accommodate a substantially greater volume (scale) and variety (scope) of UGD before they experience diminishing returns.<sup>144</sup> For instance, Netflix’s movie preference predictions continuously improve through the collection of movie preference data,<sup>145</sup> contextual data about

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<sup>141</sup> See Pajkovic, *supra* note 128, at 218; see also Spandana Singh, *Why Am I Seeing This?*, NEW AM. (Mar. 25, 2020), <http://newamerica.org/oti/reports/why-am-i-seeing-this/> [<https://perma.cc/TM8R-9HEG>].

<sup>142</sup> See Singh, *supra* note 141.

<sup>143</sup> See *id.* Netflix’s recommendation system is an important contributor to its revenue generation model, driving approximately 80% of the hours of content streamed on the platform. See Gomez-Uribe & Hunt, *supra* note 133, at 5.

<sup>144</sup> See CRÉMER ET AL., *supra* note 18, at 104 (“In general, the more complex an algorithm is and the richer the data it uses is, the more data (‘rows’) are needed to reach the level of decreasing returns.”); Christopher Mims, *Why the Only Thing Better Than Big Data Is Bigger Data*, QUARTZ (Feb. 3, 2014), <https://qz.com/169206/why-the-only-thing-better-than-big-data-is-bigger-data/> [<https://perma.cc/M8ZN-PFG5>]; see also Gediminas Adomavicius et al., *Context-Aware Recommender Systems*, AI MAG., Sept. 2011, at 67, 68 (noting that recommender systems may perform better by incorporating context); Iván Cantador et al., *Cross-Domain Recommender Systems*, in RECOMMENDER SYS. HANDBOOK 919, 926 (2d ed. 2015) (noting that recommender systems may perform better by incorporating different domains).

<sup>145</sup> See Enric Junqué de Fortuny et al., *Predictive Modeling With Big Data: Is Bigger Really Better?*, 1 BIG DATA 215, 216 (2013).

movie preferences (such as time and location), and even preference data from non-movie domains (such as music or literature).<sup>146</sup>

### C. Diversification

Diversification occurs when data platforms repurpose the UGD from one service to develop and improve (i.e., optimize and personalize) other services.<sup>147</sup> Diversification reinforces the network effects discussed so far: the more data platforms diversify their services, the more users and data-generating utilization these services attract, which empowers the platforms to diversify their services even further.<sup>148</sup> Data platforms generate value through service diversification in two interrelated ways: amplification and synergy.<sup>149</sup>

First, amplification: by diversifying their services, data platforms amplify the value of already-harvested UGD by recycling and

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<sup>146</sup> In the past, Facebook and Netflix created avenues for sharing UGD with each other for their mutual benefit. See Alex Hern, *Facebook Shared Private User Messages with Netflix and Spotify*, GUARDIAN (Dec. 19, 2018), <http://www.theguardian.com/technology/2018/dec/19/facebook-shared-user-data-private-messages-netflix-spotify-amazon-microsoft-sony> [<https://perma.cc/338D-CVSM>].

<sup>147</sup> See STIGLER FINAL REPORT, *supra* note 18, at 37 (“Firms can apply machine learning to extensive data sets to improve their products and expand their activities into new areas.”); see also Monopolies Commission, *Competition Policy: The Challenge of Digital Markets, Special Report by the Monopolies Commission Pursuant to Section 44(1)(4) of the Act Against Restraints on Competition*, MONOPOLKOMMISSION (June 1, 2015), <https://www.monopolkommission.de/index.php/en/press-releases/52-competition-policy-the-challenge-of-digital-markets> [<https://perma.cc/HJV7-URXR>]. The same dynamic also applies to a single service that has different features or functionalities. See, e.g., *supra* notes 96–97 and accompanying text.

<sup>148</sup> See Barbara Engels, *Data Portability Among Online Platforms*, 5 J. INTERNET REGUL. 1, 6–7 (2016) (“[I]n addition to offering better quality, [the platform will] be able to offer more services than before (higher variety indicated by broader triangle), since more users imply more heterogeneity in preferences and hence more demand for services, which are enabled by a larger network.”).

<sup>149</sup> Note that diversification is not the only possible way to achieve these effects. Data platforms can amplify their existing services and create data synergies while also extending its data sources in other ways, such as by acquiring UGD from third parties. See Chris Jay Hoofnagle & Jan Whittington, *Free: Accounting for the Costs of the Internet’s Most Popular Price*, 61 UCLA L. REV. 606, 647 (2014). Additionally, while this goes beyond the topic of this Article, it is important to recognize that the efficiencies in data linkage extend beyond UGD. See, e.g., OECD SECRETARIAT, *BIG DATA: BRINGING COMPETITION POLICY TO THE DIGITAL ERA 6* (2016) (defining “data-fusion”) (note submitted as background material for the 126<sup>th</sup> meeting of the OECD Competition Committee).

utilizing it for a different purpose.<sup>150</sup> The same query data that Google Search uses to optimize its spellchecking functionality also optimizes spellchecking across many other Google services, such as Docs, Translate, and Gmail.<sup>151</sup> Similarly, Netflix could launch a new music streaming service and improve its recommendation systems by utilizing the viewing data that it already collected through its existing movie streaming service.<sup>152</sup>

Second, data platforms can diversify their services through UGD-driven synergy. By merging (also known as fusing or linking) UGD from various services, platforms can launch completely new services with values that exceed the aggregated value of the input services in isolation.<sup>153</sup> For example, by merging user content from

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<sup>150</sup> See Rubinfeld & Gal, *Access Barriers*, *supra* note 92, at 372 (“[D]ata set[s] could be valuable to many different users, operating in unrelated and distinct markets.”); Shelanski, *supra* note 83, at 1677 (“Google’s scale and scope might appear to give it substantial power in a wide range of markets . . .”); DATA-DRIVEN INNOVATION, *supra* note 16, at 27; *Data Is Giving Rise to a New Economy*, ECONOMIST (May 6, 2017), <https://www.economist.com/briefing/2017/05/06/data-is-giving-rise-to-a-new-economy> [<https://perma.cc/KD2Q-YXXP>].

<sup>151</sup> See *Privacy & Terms – Privacy Policy*, GOOGLE (Dec. 15, 2022), <https://policies.google.com/privacy?hl=en-US> [<https://perma.cc/8LAQ-F4M3>] (“[U]nderstanding which search terms are most frequently misspelled helps us improve spell-check features used across our services.”); see also Warzel & Ngu, *supra* note 21; Prüfer & Schottmüller, *supra* note 73, at 989 n.25.

<sup>152</sup> See Jesse Damiani, *Black Mirror: Bandersnatch Could Become Netflix’s Secret Marketing Weapon*, VERGE (Jan. 2, 2019), <https://www.theverge.com/2019/1/2/18165182/black-mirror-bandersnatch-netflix-interactive-strategy-marketing> [<https://perma.cc/BV36-8ZN7>] (“Netflix [] knows the music [users] prefer. That could pave the way to data-mining deals with the likes of Spotify or Apple Music . . .”); Puja Deshmukh & Geetanjali Kale, *Music and Movie Recommendation System*, 61 INT. J. ENG’G TRENDS & TECH. 178, 178–81 (2018) (considering the same features for music and movie recommenders); Narechania, *supra* note 108, at 1583 (“[M]achine-learning-based applications seem computationally subadditive.”); Cantador et al., *supra* note 144, at 7.

<sup>153</sup> See DATA-DRIVEN INNOVATION, *supra* note 16, at 29.

The diversification of services leads to even better insights if data linkage is possible. This is because data linkage enables ‘super-additive’ insights, leading to increasing ‘returns to scope.’ Linked data is a means to contextualise data and thus a source for insights and value that are greater than the sum of its isolated parts (data silos).

*Id.* See also OECD SECRETARIAT, *supra* note 149; STUCKE & GRUNES, *supra* note 18, at 21; McIntosh, *supra* note 18, at 202; Cockburn et al., *supra* note 119, at 2; SHALEV-SHWARTZ & BEN-DAVID, *supra* note 60, at 22; MAYER-SCHÖNBERGER & CUKIER, *supra* note 67, at 92–95; Nathan Newman, *Taking on Google’s Monopoly Means Regulating Its Control of User Data*, HUFFINGTON POST (Sept. 24, 2013),

Google Calendar with location data from Google Maps, Google could offer a new feature allowing users to set their routes as events in Google Calendar, thereby helping them “arrive on time by knowing when to leave.”<sup>154</sup>

Diversification through UGD amplification and synergy empowers data platforms to innovate and expand the range of services they offer.<sup>155</sup> From an economic perspective, UGD serves as a “two-way complementary, such that incentives to acquire user information in one market can justify market entry in another market, and vice versa.”<sup>156</sup> This phenomenon constitutes a novel form of economies of scope.<sup>157</sup> Traditionally, economies of scope existed when a shared input in the production process made it cheaper for a single firm to produce two or more products or services relative to several separated firms.<sup>158</sup> Here, UGD is a shared input in production that enables services to increase their quality and range simultaneously.<sup>159</sup> Therefore, as with traditional economies of scope, firms in

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[https://www.huffpost.com/entry/taking-on-googles-monopol\\_b\\_3980799](https://www.huffpost.com/entry/taking-on-googles-monopol_b_3980799)  
[<https://perma.cc/U97Y-QJEZ>].

<sup>154</sup> See Abner Li, *Google Calendar Side Panel Adds Useful Google Maps Add-On*, 9TO5GOOGLE (Apr. 19, 2021), <https://9to5google.com/2021/04/19/google-calendar-maps-add-on/> [<https://perma.cc/A8TR-2Y9Z>]; STIGLER FINAL REPORT, *supra* note 18, at 43.

<sup>155</sup> See Viktoria H.S.E. Robertson, *Antitrust Market Definition for Digital Ecosystems*, in COMPETITION POLICY IN THE DIGITAL ECONOMY 4 (2021) (“What plays into the hands of the more expansive ecosystems is their reliance on user data for various services.”); MARC BOURREAU, SOME ECONOMICS OF DIGITAL ECOSYSTEMS 2–3 (2020) (discussing “product ecosystems”) (paper submitted as background material to the 134<sup>th</sup> meeting of the OECD Competition Committee).

<sup>156</sup> Prüfer & Schottmüller, *supra* note 73, at 970.

<sup>157</sup> See, e.g., STIGLER FINAL REPORT, *supra* note 18, at 37 (“Firms may also be able to leverage the data, or the insights due to machine learning, that they receive from an existing service to enter into an adjacent market with a higher quality product, demonstrating a novel form of economies of scope.”); HM TREASURY, THE ECONOMIC VALUE OF DATA: DISCUSSION PAPER 6 (2018), [https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment\\_data/file/731349/20180730\\_HMT\\_Discussion\\_Paper\\_-\\_The\\_Economic\\_Value\\_of\\_Data.pdf](https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/731349/20180730_HMT_Discussion_Paper_-_The_Economic_Value_of_Data.pdf) [<https://perma.cc/W36M-BQFA>] (“Merging two complementary datasets may produce more insight than keeping them separate.”).

<sup>158</sup> See John C. Panzar & Robert D. Willig, *Economies of Scope*, 71 AM. ECON. REV. 268, 268–72 (1981); Elizabeth E. Bailey & Ann F. Friedlaender, *Market Structure and Multiproduct Industries*, 20 J. ECON. LIT. 1024, 1024–48 (1982).

<sup>159</sup> See CRÉMER ET AL., *supra* note 18, at 33 (“[E]conomies of scope can arise from the possession of data which would enable, for instance, the design of a new service using an individual’s data or the training of a new machine-learning algorithm.”); Yong Lim, *Tech*

UGD-driven markets find expanding their business into multiple product and service markets cost-beneficial.<sup>160</sup>

Furthermore, because UGD-driven diversification is dictated by the linkability of datasets rather than physical product attributes, firms may venture far into seemingly unrelated areas—a trend that may seem perplexing from a traditional product-market point of view.<sup>161</sup> For example, consider the growth of the Amazon empire. Starting in 1995 as an online bookstore, Amazon expanded from books into music and video by 1998, and then to general retail by

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*Wars: Return of the Conglomerate Throwback or Dawn of a New Series for Competition in the Digital Era?*, 19 J. KOR. L. 47, 58 (2020); see also Charles A. Miller, *Big Data and the Non-Horizontal Merger Guidelines*, 107 CAL. L. REV. 309, 311 (2019); Niraj Dawar, *Marketing in the Age of Alexa*, HARV. BUS. REV. (May 2018), <https://hbr.org/2018/05/marketing-in-the-age-of-alexa> [<https://perma.cc/Q3PQ-AT7A>]; MARC BOURREAU ET AL., *BIG DATA AND COMPETITION POLICY: MARKET POWER, PERSONALISED PRICING, AND ADVERTISING: PROJECT REPORT 34* (2017), <https://cerre.eu/publications/big-data-and-competition-policy/> [<https://perma.cc/3ZD2-BHFT>]; Maurice E. Stucke & Ariel Ezrachi, *When Competition Fails to Optimize Quality: A Look at Search Engines*, 18 YALE J.L. & TECH. 70, 85 (2016). Alongside UGD, other resources can also serve as shareable production inputs. See Bourreau & de Streel, *supra* note 59, at 10; Varian, *Recent Trends*, *supra* note 17, at 818; MOORE & TAMBINI, *supra* note 95, at 35; Venkat Venkatraman, *Alphabet Isn't a Typical Conglomerate*, HARV. BUS. REV. (Aug. 18, 2015), <https://hbr.org/2015/08/alphabet-isnt-a-typical-conglomerate> [<https://perma.cc/69XH-QV4H>]; BOURREAU, *SOME ECONOMICS OF DIGITAL ECOSYSTEMS*, *supra* note 155, at 3.

<sup>160</sup> See Bourreau & de Streel, *supra* note 59; Charles I. Jones & Christopher Tonetti, *Nonrivalry and the Economics of Data*, 110 AM. ECON. REV. 2819, 2855 (2020) (“[B]ecause firms see increasing returns to scale associated with data and, perhaps more importantly, because of the nonrivalry of data, firms in this economy would like to merge into a single economy-wide firm.”); AMNESTY INT’L, *supra* note 18, at 14 (“Google and Facebook are also expanding into new areas that extend the reach of their data collection.”); BOURREAU, *SOME ECONOMICS OF DIGITAL ECOSYSTEMS*, *supra* note 155, at 4. However, economies of scope will lead to the expansion of the firm only to the extent that the markets for sharable inputs do not function properly. Otherwise, the firms could trade their excess capacity in sharable inputs instead of diversifying into new markets. See David J. Teece, *Economies of Scope and the Scope of the Enterprise*, J. ECON. BEHAVIOR & ORG. 223, 223–47 (1980). Because of privacy, intellectual property, and other limitations, UGD markets are imperfect at best. See discussion *infra* Part II.

<sup>161</sup> See Bourreau & de Streel, *supra* note 59, at 9 (“With data-driven network effects, firms thus have incentives to diversify into connected markets. Note that two markets can be connected because they share the same data, while being weakly related from a product market definition point of view.”); Panos Constantinides et al., *Platforms and Infrastructures in the Digital Age*, 29 INFO. SYS. RSCH. 1, 2 (2018) (“[D]igital complements are product-agnostic.”); Graef, *supra* note 108, at 493 (giving the example of Google and Nest as connected yet unrelated markets); STUCKE & GRUNES, *supra* note 18, at 128.

1999.<sup>162</sup> Since then, Amazon has exploded into various areas, including payment services, cloud computing, and product delivery.<sup>163</sup> Along with other data platforms of its caliber, Amazon’s successful diversification strategy is heavily empowered by UGD network effects.<sup>164</sup> As Paolo Aversa and co-authors explain:

[T]he main strategic choice of a firm is “business model diversification.” . . . By increasing adoption between and within customer groups, the firm attracts new customers to the platform and therefore contributes to boosting the “customer base” (i.e., the accumulated stock of customers) over time. This is not only associated with firm growth, but it also provides greater access to customer data which, more importantly, can be utilized to enhance “customer profiling and customization”—thus offering personalized consumption experiences.<sup>165</sup>

As data platforms gather richer and more varied sets of UGD from their diversified services, they gain fuller insight into user preferences, which in turn enables them to address these preferences with more sophistication.<sup>166</sup> Over time, with sufficient UGD—stemming from online offerings and offline “smart” Internet-of-Things devices<sup>167</sup>—services will become far more capable of

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<sup>162</sup> See Paolo Aversa et al., *Customer Complementarity in the Digital Space: Exploring Amazon’s Business Model Diversification*, 54 LONG RANGE PLANNING 1, 6 tbl.1 (2021).

<sup>163</sup> See Andrew Ross Sorkin, *Conglomerates Didn’t Die. They Look Like Amazon.*, N.Y. TIMES (June 19, 2017) <https://www.nytimes.com/2017/06/19/business/dealbook/amazon-conglomerate.html> [<https://perma.cc/5XL6-XXZC>]; Khan, *supra* note 88, at 754.

<sup>164</sup> See Lim, *supra* note 159, at 56; Bourreau & de Streel, *supra* note 59, at 4; Aversa et al., *supra* note 162, at 18.

<sup>165</sup> Aversa et al., *supra* note 162, at 14. See also Mohan Subramaniam et al., *Competing in Digital Ecosystems*, 62 BUS. HORIZONS 83, 85 (2019).

<sup>166</sup> See MOORE & TAMBINI, *supra* note 95, at 28 (“The more detailed the data, the wider the range of transactions, the bigger the user sample, and the greater the company’s cumulative analytics experience, the better: quantity drives quality.”); see also Maurice E. Stucke & Allen P. Grunes, *Debunking the Myths Over Big Data and Antitrust*, 5 ANTITRUST CHRON. 2, 2–5 (2015); STIGLER FINAL REPORT, *supra* note 18, at 48; DATA-DRIVEN INNOVATION, *supra* note 16, at 10. *But see* Stucke & Grunes, *supra* note 18, at 78 (emphasizing that not all datasets are linkable).

<sup>167</sup> See SYMONS & BASS, *supra* note 11, at 24 (“[Internet-of-Things] firms that collect this data will rely upon data processes to connect data generated from multiple devices (connected homes, cars, wearables etc.), and in doing so will be able to generate profiles

helping users with general utility recommendations in sensitive areas such as health, entertainment, business, and even romance.<sup>168</sup> Meta's new service, Facebook Dating, provides an example of these dynamics.<sup>169</sup>

Until recently, Facebook utilized UGD collected within its platform to improve context-specific recommendation systems.<sup>170</sup> It used content-viewing data to recommend additional content, social-connection data to recommend additional connections with friends, and browsing and engagement data to recommend advertisements.<sup>171</sup> However, with Facebook Dating, Meta took Facebook's recommender systems one step further. Facebook Dating leverages Meta's deep understanding of users across many domains—cultural interests, social connections, and behavioral history—to suggest potential dating partners to users based on who they are (algorithmically) most likely to fall in love with.<sup>172</sup> For instance, if Joe and Alice indicated that they both live in the SoHo neighborhood of New

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of individual preferences and [behaviors] with a level of detail that was not possible before.”); HM TREASURY, *supra* note 157, at 4–5; LEE, *supra* note 58, at 108–12 (explaining how China has an advantage in Internet-of-Things UGD).

<sup>168</sup> See Yuval Noah Harari, *Yuval Noah Harari on Big Data, Google and the End of Free Will*, FIN. TIMES (Aug. 26, 2016), <https://www.ft.com/content/50bb4830-6a4c-11e6-ae5b-a7cc5dd5a28c> [<https://perma.cc/5WZE-T9K2>]; Vlad Savov, *Google's Selfish Ledger Is an Unsettling Vision of Silicon Valley Social Engineering*, VERGE (May 17, 2018), <https://www.theverge.com/2018/5/17/17344250/google-x-selfish-ledger-video-data-privacy> [<https://perma.cc/QPF7-U3PP>]; see also Delacroix & Veale, *supra* note 67, at 94.

<sup>169</sup> See BOURREAU, SOME ECONOMICS OF DIGITAL ECOSYSTEMS, *supra* note 155, at 4; Nathan Sharp, *It's Facebook Official, Dating Is Here*, META (Nov. 22, 2021), <https://about.fb.com/news/2019/09/facebook-dating/> [<https://perma.cc/UW8M-EWHR>] (explaining how Facebook Dating uses social connections UGD from both Facebook and Instagram and on preference profiles which are gathered from users' Facebook “likes” and activities); Louise Matsakis, *Facebook Is Testing Its Dating Service. Here's How It's Different From Tinder*, WIRED (Nov. 8, 2018), <https://www.wired.com/story/facebook-dating-how-it-works/> [<https://perma.cc/KJP4-R3PP>] (“By utilizing the trove of data it already has about users, Facebook has the ability to become a powerful player in the online dating space.”).

<sup>170</sup> See Sarah Perez, *Facebook Partially Documents Its Content Recommendation System*, TECHCRUNCH (Aug. 31, 2020), <https://social.techcrunch.com/2020/08/31/facebook-partially-documents-its-content-recommendation-system/> [<https://perma.cc/NL63-BYQF>].

<sup>171</sup> See *id.*; cf. CHARU C. AGGARWAL, RECOMMENDER SYSTEMS: THE TEXTBOOK 439 (2016) (discussing how computational advertisement is closely linked to recommender systems).

<sup>172</sup> See Matsakis, *supra* note 169.



York City, are devoted *New York Times* crossword solvers, love to go dancing, and read the same fantasy books, Facebook might recommend them to one another—and might even get compelling results.

Although it sounds radical, Facebook Dating is merely an appetizer for what the future of cross-domain UGD-analytics has in store. Speculating about the future of dating-recommender systems, Yuval Noah Harari wrote in the *Financial Times*:

[E]ventually people may give algorithms the authority to make the most important decisions in their lives, such as who to marry. . . . “Listen, Google,” I will say, “both John and Paul are courting me. I like both of them, but in a different way, and it’s so hard to make up my mind. Given everything you know, what do you advise me to do?” And Google will answer: “Well, I know you from the day you were born. I have read all your emails, recorded all your phone calls, and know your favourite films, your DNA, and the entire biometric history of your heart. I have exact data about each date you went on, and I can show you second-by-second graphs of your heart rate, blood pressure and sugar levels whenever you went on a date with John or Paul. And, naturally enough, I know them as well as I know you. Based on all this information, on my superb algorithms and on decades’ worth of statistics about millions of relationships—I advise you to go with John, with an 87 per cent probability of being more satisfied with him in the long run.”<sup>173</sup>

Already, personal digital assistant devices are becoming smarter and more proactive in users’ daily lives. Amazon’s Alexa can recommend to a user not only which music they are likely to want to hear or which movie they are likely to want to watch but also when they are likely to be interested in these activities.<sup>174</sup> Because digital

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<sup>173</sup> Harari, *supra* note 168.

<sup>174</sup> For example, the Alexa Hunches feature detects repetitive user behavior and suggests ways to automate it. See Bret Kinsella, *Amazon Alexa Latent Goals Feature Will Predict*

assistants are the ultimate personalization machines, the most successful assistants are likely to emerge from the firms that possess the largest and richest databases of UGD.<sup>175</sup> Firms will compete in the digital assistant marketplace through an aggressive diversification strategy.<sup>176</sup>

## II. COMPETITION DYNAMICS

*The goal is efficiency, not competition. The ultimate goal is that there be efficiency.*<sup>177</sup>

*Lawrence H. Summers,  
Former United States Secretary of the Treasury*

This Part explores the impact of traditional and UGD network effects on market competition dynamics. It shows that as the

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*Customer Objectives and Proactively Suggest Follow-on Actions and Even Aid in Skill Discovery*, VOICEBOT.AI (Nov. 11, 2020, 11:00 AM), <https://voicebot.ai/2020/11/11/amazon-alexa-latent-goals-feature-will-predict-customer-objectives-and-proactively-suggest-follow-on-actions-and-even-aid-in-skill-discovery/> [<https://perma.cc/MCS2-BCHH>]; Khari Johnson, *AI Weekly: Recommendation Engines Are Driving Amazon's Alexa Hardware Strategy*, VENTUREBEAT (Sept. 27, 2019, 1:59 PM), <https://venturebeat.com/2019/09/27/ai-weekly-recommendation-engines-are-driving-amazons-alexa-hardware-strategy/> [<https://perma.cc/ATL3-T39D>]; see also Niraj Dawar, *Marketing in the Age of Alexa*, HARV. BUS. REV., May–June 2018, <https://hbr.org/2018/05/marketing-in-the-age-of-alexa> [<https://perma.cc/H53P-NAF6>] (“A platform serves consumers by constantly anticipating their needs. To do that it must collect granular data on their purchasing patterns and product use and try to understand their goals . . .”).

<sup>175</sup> See Maurice E. Stucke & Ariel Ezrachi, *How Digital Assistants Can Harm Our Economy, Privacy, and Democracy*, 32 BERKELEY TECH. L.J. 1239, 1287 (2017) [hereinafter Stucke & Ezrachi, *How Digital Assistants*]; Ariel Ezrachi & Maurice E. Stucke, *Is Your Digital Assistant Devious?* (Oxford Legal Studies Research Paper No. 52/2016; Univ. of Tenn. Legal Studies Research Paper No. 304, Aug. 23, 2016) [hereinafter Ezrachi & Stucke, *Digital Assistant Devious*], [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2828117](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2828117) [<https://perma.cc/HXB7-Y4S9>]; see also ARIEL EZRACHI & MAURICE E. STUCKE, VIRTUAL COMPETITION: THE PROMISE AND PERILS OF THE ALGORITHM-DRIVEN ECONOMY 11–21 (2016) [hereinafter EZRACHI & STUCKE, PROMISE AND PERILS].

<sup>176</sup> See STUCKE & GRUNES, *supra* note 18, at 38 (“[C]ompanies, with data-driven business models, are increasingly undertaking strategies to obtain and sustain a competitive advantage. Companies strive to acquire a ‘big data-advantage’ over rivals.”).

<sup>177</sup> Lawrence H. Summers, *Competition Policy in the New Economy*, 69 ANTITRUST L.J. 353, 358 (2001).

economics of platforms shift from the former to the latter, market competition declines, and market concentration intensifies.

### A. *In the Market*

Economic theory suggests that competition in markets characterized by traditional network effects will likely give rise to a monopoly.<sup>178</sup> Because a network good's value increases when other users also utilize it, once a single provider has amassed more users than its rivals, that provider is likely to gain a competitive edge and attract even more users at its rivals' expense.<sup>179</sup> Therefore, as the lead network grows, its competing networks get smaller. Economists call this phenomenon "tipping," which is "the tendency of one system to pull away from its rivals in popularity once it has gained an initial edge."<sup>180</sup>

Tipping played a historic role in re-establishing the Bell System monopoly after a long market competition with "independent" telephone networks.<sup>181</sup> Starting in the mid-1980s, following the expiration of the original telephone patents (which had isolated Bell's

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<sup>178</sup> Assuming the network is privately owned. See P.A. Geroski, *Competition in Markets and Competition for Markets*, 3 J. INDUS. COMPETITION & TRADE 151, 156 (2003).

<sup>179</sup> See Stanley M. Besen & Joseph Farrell, *Choosing How to Compete: Strategies and Tactics in Standardization*, 8 J. ECON. PERSPS. 117, 118–19 (1994); cf. Mark J. Roe, *Chaos and Evolution in Law and Economics*, 109 HARV. L. REV. 641, 644 (1996).

<sup>180</sup> Katz & Shapiro, *Systems Competition*, *supra* note 44, at 105–06. See also SHAPIRO & VARIAN, *supra* note 13, at 175–76 (explaining how, when multiple firms compete in a market where there is strong positive feedback, "the strong get stronger and the weak get weaker," and the market tends to "tip" in favor of one player). Tipping may even be triggered by users' mere expectations. See Michael L. Katz & Carl Shapiro, *Product Introduction with Network Externalities*, 40 J. INDUS. ECON. 55, 55–56 (1992); Michael Katz & Carl Shapiro, *Technology Adoption in the Presence of Network Externalities*, 94 J. POL. ECON. 822, 825 (1986). For this reason, companies sometimes have the perverse incentive to use deceptive advertising tactics to create false consumer expectations in an attempt to initiate the process of market tipping. See Robert Prentice, *Vaporware: Imaginary High-Tech Products and Real Antitrust Liability in a Post-Chicago World*, 57 OHIO ST. L.J. 1163, 1163–64 (1996).

<sup>181</sup> For a detailed review of this history, see SHAPIRO & VARIAN, *supra* note 13, at 212–14; Robert Bornholz & David S. Evans, *The Early History of Competition in the Telephone Industry*, in *BREAKING UP BELL: ESSAYS ON INDUSTRIAL ORGANIZATION AND REGULATION* 7, 13 (1983); Richard Gabel, *The Early Competitive Era in Telephone Communication, 1893–1920*, 34 L. & CONTEMP. PROBS. 340, 344 (1969) (reporting three million independent lines in 1907, compared with 3.1 million Bell lines); Spulber & Yoo, *Mandating Access*, *supra* note 56, at 1892–96.

monopoly from competition), independent telephone companies sprouted to compete with Bell's established network.<sup>182</sup> At the local-call level, the Bell System and the independent telephone companies competed on equal terms.<sup>183</sup> However, at the long-distance call level, Bell had a clear size advantage.<sup>184</sup> By withholding interconnection to their long-distance network from local competitors while simultaneously allowing access to nonaffiliated parties on limiting terms, the Bell System managed to tip the market to its advantage.<sup>185</sup> Over time, this advantage enabled Bell (later AT&T) to regain dominance at the local and the long-distance levels and eventually monopolize the entire telephone market.<sup>186</sup>

Tipping also occurs in the presence of UGD network effects.<sup>187</sup> A more extensive UGD network platform will likely tip the market

<sup>182</sup> See SHAPIRO & VARIAN, *supra* note 13, at 212.

<sup>183</sup> See Spulber & Yoo, *Mandating Access*, *supra* note 56, at 1892–96.

<sup>184</sup> See SHAPIRO & VARIAN, *supra* note 13, at 213 (calling this a “winning strategy”).

<sup>185</sup> See *id.*; see also Shelanski & Sidak, *supra* note 44, at 8. Nevertheless, smaller networks may sometimes survive and co-exist alongside the dominant network if the former has inherent value that is substantial enough to offset their low network value. See Besen & Farrel, *supra* note 179, at 118.

<sup>186</sup> AT&T's legendary president, Theodore Newton Vail, cleverly reinforced these economic dynamics with the well-coordinated “One System, One Policy, Universal Service” advertising campaign. See Robert MacDougall, *AT&T's Long-Distance Network as an Organizational and Political Strategy*, 80 BUS. HIST. REV. 297, 321 (2006) (citing historian Roland Marchand calling Vail's campaign “the most celebrated of the large-scale institutional advertising campaigns of the early twentieth century”); *id.* at 303 (“[Vail insisted that] the theory was evolved and developed before the business, and the business has been developed on that theory.”).

<sup>187</sup> See DIG. COMPETITION, *supra* note 18, at 4 (“In many cases, digital markets are subject to ‘tipping’ in which a winner will take most of the market.”); STUCKE & GRUNES, *supra* note 18, at 7 (“Data-driven markets can lead to a ‘winner takes all’ result where concentration is a likely outcome of market success.”); DATA-DRIVEN INNOVATION, *supra* note 16, at 7; see also Timothy J. Brennan, *Why Regulated Firms Should Be Kept Out of Unregulated Markets: Understanding the Divestiture in United States v. AT&T*, 32 ANTITRUST BULL. 741, 741–43 (1987). Numerous commenters have suggested that digital markets have “natural monopoly” characteristics. See, e.g., Sukhayl Niyazov, *AI-Powered Monopolies and the New World Order*, MEDIUM (June 28, 2019), <https://towardsdatascience.com/ai-powered-monopolies-and-the-new-world-order-1c56cfc76e7d> [<https://perma.cc/BC5D-KBSG>] (“The problem with the AI-powered economy is that industries naturally tend towards monopolization because of the positive feedback loop that is generated as a result of AI's dependence on data.”); Sukhayl Niyazov, *Don't Break Up Big Tech*, MEDIUM (Feb. 27, 2020), <https://medium.com/swlh/dont-break-up-big-tech-fb17590f30f1> [<https://perma.cc/H8U9-U3K7>] (“In the data-driven economy, the process of monopolization is inevitable.”); Narechania, *supra* note 108, at 1585; Oren

to its advantage and overtake smaller UGD networks. For example, by controlling the most significant volume of user inquiry data, Google Search controls nearly 80% of the international search market amongst desktop search engines.<sup>188</sup> Similarly, Google Maps, which has the largest reservoir of traffic location data (especially after acquiring Waze and its passionate community of data-generating users), controls approximately 70% of the web-mapping market.<sup>189</sup> In the autonomous vehicles market, competition over market dominion is still evolving.<sup>190</sup> Whereas brands like Tesla have a greater volume (i.e., scale) of driver-generated data, competitors such as Waymo have a greater variety (i.e., scope) of better quality driving data due to smarter sensor technology.<sup>191</sup> Once one of the competing brands captures a significant UGD advantage, the market for autonomous vehicles might tip to its advantage.<sup>192</sup>

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Bracha & Frank Pasquale, *Federal Search Commission? Access, Fairness, and Accountability in the Law of Search*, 93 CORNELL L. REV. 1149, 1180–81 (2008); Steven Weber & Gabriel Nicholas, *Data, Rivalry and Government Power: Machine Learning Is Changing Everything*, 14 GLOBAL ASIA 22, 25–26 (2019). Many commentators put a particular emphasis on the web-search market. *See, e.g.*, Andrei Hagiu & Julian Wright, *When Data Creates Competitive Advantage*, HARV. BUS. REV., Jan.–Feb. 2020, <https://hbr.org/2020/01/when-data-creates-competitive-advantage>

[<https://perma.cc/W5YU-YXWY>]; FRANCESCO DUCCI, NATURAL MONOPOLIES IN DIGITAL PLATFORM MARKETS 5, 47–75 (2020); Ioannis Lianos & Eugenia Motchenkova, *Market Dominance and Search Quality in the Search Engine Market*, 9 J. COMP. L. & ECON. 419, 435 (2013); *cf.* Eric K. Clemons & Nehal Madhani, *Regulation of Digital Businesses with Natural Monopolies*, 27 J. MGMT. INFO. SYS. 43, 45 (2011); Herbert Hovenkamp, *Antitrust and Platform Monopoly*, 130 YALE L.J. 1952, 1971 (2021) (“Few platforms are natural monopolies.”).

<sup>188</sup> *See Market Share of Leading Desktop Search Engines Worldwide From January 2015 to July 2023*, STATISTA, <https://www.statista.com/statistics/216573/worldwide-market-share-of-search-engines/> [<https://perma.cc/D7DJ-33RR>] (last visited Sept. 21, 2023).

<sup>189</sup> *See* Alper D. Karakas, *Google Maps: Friendly Giant?*, ECON. REV. (Mar. 24, 2019), <https://theconreview.com/2019/03/24/google-mapsfriendly-giant/> [<https://perma.cc/5FMB-XHZJ>].

<sup>190</sup> *See* Timothy B. Lee, *Who Will Win the Self-Driving Race? Here Are Eight Possibilities*, ARS TECHNICA (Apr. 19, 2021, 7:00 AM), <https://arstechnica.com/cars/2021/04/who-will-win-the-self-driving-race-here-are-8-possibilities/> [<https://perma.cc/N8VY-TEZL>].

<sup>191</sup> *See* LEE, *supra* note 58, at 131–32 (comparing Tesla’s collaborative approach with Google’s Waymo in-house approach and noting that the “different approaches have led to a massive data gap between” Tesla and Google).

<sup>192</sup> *See* Yarrow Bouchard, *Tesla’s Deep Learning at Scale: Using Billions of Miles to Train Neural Networks*, MEDIUM (May 6, 2019), <https://towardsdatascience.com/teslas-deep-learning-at-scale-7eed85b235d3> [<https://perma.cc/ZW9L-CLXE>] (claiming that

When tipping occurs—whether because of network effects or other forms of scale economics—the emerging market monopolization is largely considered efficient and, therefore, socially desirable.<sup>193</sup> As Mark Lemley and David McGowan explain, “efforts to forestall tipping would result in suboptimal heterogeneity among systems and losses in terms of unrealized efficiencies.”<sup>194</sup> For this reason, network markets are sometimes called “natural” monopolies, implying that multi-company competition in such markets is often unattainable.<sup>195</sup>

While competition dynamics in markets characterized by either traditional or UGD-driven network effects are similar (both are susceptible to market tipping) there are important differences between them. Traditional network markets are often subject to two other competitive forces that constrain the reach and resulting market concentration of tipping. One of these forces is competition “across the market,” which refers to the competitive dynamics in complementary markets and markets traditionally considered “unrelated” to the network good. Another competition force is competition “for the market,” which refers to the competition dynamics between

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generally, “more training data leads to better performance,” unless there are different types of data that are needed for different sub-markets); *supra* note 187 and accompanying text.  
<sup>193</sup> See Nicholas Economides, Comment to the Antitrust Division of the U.S. Dep’t of Just. on the Proposed Settlement in the Current Microsoft Case (Jan. 24, 2002, 2:22 PM), <https://www.justice.gov/atr/microsoft-tunney-act-comment-nicholas-s-economides> [<https://perma.cc/8NNB-96J7>] (“In industries with significant network externalities, under conditions of incompatibility between competing platforms, monopoly may maximize social surplus.”).

<sup>194</sup> Lemley & McGowan, *Legal Implications*, *supra* note 44, at 497.

<sup>195</sup> Tipping into a monopoly is not a network-centric phenomenon. Economists have long identified tipping in conventional scale economy markets. Unlike network effects, which are demand-side (consumption-based) effects, economics of scale are supply-side (i.e., production-based) effects: they refer to the cost advantage that companies reap by increasing output. While analytically distinct, economies of scale and network effects often appear together (as in the telecommunication market). In doing so, they reinforce these markets’ tipping tendencies. Both economic forces are contributing factors to the “new” information economy which is distinguishable from the classic economic paradigm that posits diminishing (as opposed to increasing) returns to scale. See ROBERT S. PINDYCK & DANIEL L. RUBINFELD, *MICROECONOMICS* 187 (3d ed. 1995); W. Brian Arthur, *Increasing Returns and the New World of Business*, HARV. BUS. REV., July–Aug. 1996, <https://hbr.org/1996/07/increasing-returns-and-the-new-world-of-business> [<https://perma.cc/L36Z-T6JX>]; see generally W. BRIAN ARTHUR, *INCREASING RETURNS AND PATH DEPENDENCE IN THE ECONOMY* (1994).

incumbent network monopolists and nascent “disruptive” competitors. As explained in the following two sections, both competitive forces are becoming far less stable in UGD network effect markets compared to traditional network effect markets.

### B. Across the Market

Traditional network effect markets are clearly bounded. When AT&T monopolized the telephone industry, policymakers could conceptually separate the so-called *natural monopoly* portion of the business, namely the telecommunication services, from other complementing businesses, such as equipment manufacturing.<sup>196</sup> Whereas the former market is allegedly susceptible to tipping and monopolization, the latter is not and is likely to be perfectly competitive. According to the Chicago School’s classic one-monopoly profit theory, monopolists are unlikely to extend or leverage their monopoly and upset competition in complementary markets because doing so would diminish consumer demand for their primary monopoly good and would therefore diminish total profits.<sup>197</sup> Conversely, in some cases, monopolies have the opposite incentive of fostering vibrant competition in complementary markets because such competition would increase consumer demand for their

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<sup>196</sup> See Brennan, *supra* note 187.

<sup>197</sup> The crux of the Chicagoans critique was that any given amount of monopoly power can be used to extract only a given amount of revenue from consumers. A monopolist can either vertically integrate and split its monopoly revenues between two markets, or it can simply avoid integration and extract all its monopoly revenues in its single “primary” market. See, e.g., ROBERT H. BORK, *THE ANTITRUST PARADOX* 226–31, 372–73, 375 (1978); Ward S. Bowman, Jr., *Tying Arrangements and the Leverage Problem*, 67 *YALE L.J.* 19, 20–21 (1957); James B. Speta, *Handicapping the Race for the Last Mile?: A Critique of Open Access Rules for Broadband Platforms*, 17 *YALE J. ON REGUL.* 39, 84 (2000). While there will be cases where monopolists would find venturing into adjacent markets efficient, these cases would likely be limited to vertical relationships and justified by transaction-specific efficiencies. For an overview, see Christopher S. Yoo, *Vertical Integration and Media Regulation in the New Economy*, 19 *YALE J. ON REGUL.* 171, 190–200 (2002); William F. Baxter, *Conditions Creating Antitrust Concern with Vertical Integration by Regulated Industries—“For Whom the Bell Doctrine Tolls”*, 52 *ANTITRUST L.J.* 243, 245–46 (1983); Joseph Farrell & Philip J. Weiser, *Modularity, Vertical Integration, and Open Access Policies: Towards a Convergence of Antitrust and Regulation in the Internet Age*, 17 *HARV. J.L. & TECH.* 85, 97 (2003).

primary goods, thereby increasing their total profits.<sup>198</sup> As James Speta explains, in the broadband transmission context, “even a monopolist will have the incentive to encourage a wide variety of information services in order to increase subscribership.”<sup>199</sup>

For these reasons, even if traditional network monopolists are unlikely to face competition within their primary markets, they are still influenced by competition dynamics “across the market,” namely in adjacent markets, such as those for complementary products.<sup>200</sup> Competitive dynamics in adjacent markets help keep traditional network monopolies in check by limiting their incentives to expand and enabling regulatory authorities to oversee them.<sup>201</sup> If monopolists try to break free of regulatory limitations in their primary network markets by engaging in anticompetitive leverage into complementary markets,<sup>202</sup> as in the famous *United States v. AT&T*

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<sup>198</sup> Somewhat confusingly, this dynamic is also labeled “network effects,” albeit “indirect;” this occurs in a situation where the value for a primary good increases as better and more diverse complementary goods become available. See Katz & Shapiro, *Network Externalities*, *supra* note 44.

<sup>199</sup> Speta, *supra* note 197.

<sup>200</sup> Products are complementary to one another when users generate value from consuming them together. See, e.g., Taylan Yalcin et al., *Complementary Goods: Creating, Capturing, and Competing for Value*, 32 *MARKETING SCI.* 554, 554 (2013). The network monopolist does not “compete” with the producers of complementary products because these products are not reasonably interchangeable with the network good. See *Brown Shoe Co. v. United States*, 370 U.S. 294, 325 (1962); see also *Times-Picayune Publ’g Co. v. United States*, 345 U.S. 594, 612 n.31 (1953) (“The circle must be drawn narrowly to exclude any other product to which, within reasonable variations in price, only a limited number of buyers will turn; in technical terms, products whose ‘cross-elasticities of demand’ are small.”). Nevertheless, the network monopolists still maintain a complex competitive relationship with the producers of complements (that some call “coopetition” or a “frenemy” relationship). Moreover, in a broad economic sense, all producers compete with one another for a share of consumers’ limited wealth. See John M. Newman, *Antitrust in Zero-Price Markets: Applications*, 94 *WASH. U. L. REV.* 49, 61 (2016) (“[A]ll products could be thought of as interchangeable: customers with scarce resources must choose how to allocate those resources, and a decision to acquire one product necessitates (at the margin) giving up the opportunity to acquire another.”); David Glasner & Sean P. Sullivan, *The Logic of Market Definition*, 83 *ANTITRUST L.J.* 293, 298 (2020) (“[A]ntitrust markets are defined in terms of specific theories of anticompetitive harm.”).

<sup>201</sup> As an example, for a time, the American government considered AT&T a “natural monopoly” and regulated it as such. See Narechania, *supra* note 108, at 1560; *Verizon Commc’ns, Inc. v. FCC*, 535 U.S. 467, 475–76 (2002).

<sup>202</sup> Even in traditional network industries, market “leverage” might be efficient for various reasons. However, such efficiencies would often be transaction specific and would



antitrust case, the government can restore healthy competition “across the market” by requiring the network monopolists to divest control over the complementary businesses.<sup>203</sup>

However, unlike in traditional network markets, UGD network effect markets do not have clear boundaries with adjacent complementary markets.<sup>204</sup> As Christoph Busch, Inge Graef, Jeanette Hofmann, and Annabelle Gawer explain:

Whereas the distinction between market sectors, or between industries, used to be stable and meaningful, we see online platform firms appearing to be able to “glide” from market to market, as if, to them, the boundaries between markets were somehow porous or permeable. As digitalization enables the generation of data-driven complementarities across markets and across products and services, a better unit of

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have to overcome the efficiencies that result from keeping the complementary markets competitive. *See supra* note 200 and accompanying text.

<sup>203</sup> *See* United States v. AT&T, 552 F. Supp. 131, 200–01 (D.D.C. 1982). From the traditional Chicago School perspective, AT&T allegedly had no efficiency-enhancing justification (and thus no incentive) to vertically integrate into complementary markets, such as equipment manufacturing. *See* discussion *supra* note 198. Nevertheless, AT&T was motivated to engage in anticompetitive leverage into adjacent markets only as a means to overcome government price regulations in its primary telecommunications market. For a detailed analysis, see Brennan, *supra* note 187, at 764; Yoo, *supra* note 197, at 189–91 (“[Even Chicago School scholars have acknowledged that] a monopolist subject to rate regulation may well find it profitable to integrate vertically.”); Farrell & Weiser, *supra* note 197, at 105. For this reason, AT&T’s antitrust precedent, also known as “Baxter’s Law,” or the “Bell Doctrine,” is famously limited to regulated monopolies. *See* Baxter, *supra* note 197, at 245–46.

<sup>204</sup> *See* Nicolas Petit, *Technology Giants, The “Moligopoly” Hypothesis and Holistic Competition: A Primer* 3 (unpublished manuscript, Oct. 20, 2016), [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2856502](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2856502) [<https://perma.cc/PLC8-Q3PR>] (“[T]he tech giants are conglomerates that compete three-dimensionally as oligopolists across industries, and not within itemized relevant markets where they (inevitably) are monopolists.”); DIG. COMPETITION, *supra* note 18, at 32 (“[S]trong economies of scope are one reason why the same small number of large digital companies have successfully built ecosystems across several adjacent markets.”); *see also* DATA-DRIVEN INNOVATION, *supra* note 16, at 29; Robertson, *supra* note 155, at 5; Subramaniam et al., *supra* note 165, at 92; BOURREAU, SOME ECONOMICS OF DIGITAL ECOSYSTEMS, *supra* note 155, at 3; GALLOWAY, *supra* note 2, at 92.

analysis might be rather that of an ecosystem which can cut across markets or sectors.<sup>205</sup>

Because UGD datasets from one market (such as web search) can seamlessly be interconnected with UGD datasets from another market (such as smart home appliances), the “natural” boundaries of UGD network monopolists are becoming impossible to decipher. Thus, divesting Google from Nest is nothing like divesting AT&T from Western Electronic, even though, in both cases, the former offers information services and the latter offers physical equipment.<sup>206</sup> In the former case, the link between Google and Nest is likely efficient, whereas in the latter case, it is likely not so.

Competition across the market in a UGD-driven economy is likely to be unstable, as data platforms will gradually expand their reach into complementary markets.<sup>207</sup> Moreover, as explained in Section I.C, the tendency towards UGD-driven tipping extends far beyond complementary markets to markets of seemingly unrelated products and services.<sup>208</sup> Indeed, the markets in which Google and Nest operated before their merger were utterly unrelated to one another in the conventional antitrust sense.<sup>209</sup> In other words, the same tipping tendency traditionally bounded to primary network markets is now spreading across UGD-driven market categories, leading to the formation of natural multi-industry conglomerates.<sup>210</sup>

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<sup>205</sup> CHRISTOPH BUSCH ET AL., UNCOVERING BLINDSPOTS IN THE POLICY DEBATE ON PLATFORM POWER 13 (2021), <https://research.tilburguniversity.edu/en/publications/uncovering-blindspots-in-the-policy-debate-on-platform-power-fina> [<https://perma.cc/K5DD-6WMT>].

<sup>206</sup> Indeed, divestiture is no longer efficient in cases where a monopolist’s extension across markets is natural and efficient, such as in the presence of economies of scope. See Brennan, *supra* note 187, at 764–65; *supra* note 157 and accompanying text.

<sup>207</sup> See, e.g., STUCKE & GRUNES, *supra* note 18, at 40 (“[G]iven that data’s value depends on its volume, variety, and how quickly the data is collected and analyzed, companies will increasingly focus on opportunities to acquire a data-advantage through mergers.”); DIG. COMPETITION, *supra* note 18, at ch. 3 (recognizing the same trend); SUBCOMM., INVESTIGATION OF COMPETITION, *supra* note 18, at 9 (“Google increasingly functions as an ecosystem of interlocking monopolies.”).

<sup>208</sup> See *supra* notes 161–69 and accompanying text.

<sup>209</sup> See *supra* notes 161–69 and accompanying text.

<sup>210</sup> See *supra* notes 161–69 and accompanying text.

To appreciate fully the potential of inter-market tipping, consider the data platform WeChat, created by the multinational Chinese corporation, Tencent.<sup>211</sup> As Kai-Fu Lee explains:

Tencent painstakingly built WeChat into the world's first super-app. It became a "remote control for life" that dominated not just users' digital worlds but allowed them to pay at restaurants, hail taxis, unlock shared bikes, manage investments, book doctors' appointments, and have those doctors' prescriptions delivered to [their] door. This metastasizing functionality would blur the lines dividing our online and offline worlds, both molding and feeding off of China's alternate internet universe.<sup>212</sup>

As with traditional network effects, inter-market tipping and conglomeration are economically efficient.<sup>213</sup> Forestalling these processes might lead to the suboptimal disentanglement of compatible datasets and losses in terms of unrealized value.<sup>214</sup> However, as discussed in Part 0, there are also countervailing effects. Consolidation across markets may end up negatively impacting user welfare if UGD-driven intelligence is pursued not to realize efficiencies, but to either facilitate price discrimination and behavioral manipulation among platform users or to identify and neutralize competitive pressures "for" UGD-markets.<sup>215</sup>

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<sup>211</sup> See Jonah M. Kessel & Paul Mozur, *Video: How China Is Changing Your Internet*, N.Y. TIMES (Aug. 9, 2016) <https://www.nytimes.com/video/technology/100000004574648/china-internet-wechat.html> [<https://perma.cc/6AC9-GFDP>].

<sup>212</sup> LEE, *supra* note 58, at 59.

<sup>213</sup> See CRÉMER ET AL., *supra* note 18, at 110 ("[M]ergers can have procompetitive consequences, by allowing the provision of new services thanks to the access to richer sets of data."); DIG. COMPETITION, *supra* note 18, at 32; Carl Shapiro, *Competition and Innovation: Did Arrow Hit the Bull's Eye?*, in THE RATE & DIRECTION OF ECONOMIC ACTIVITY REVISITED 361, 365 (2012) (noting that the "synergies principle" is especially likely in the technology sector).

<sup>214</sup> See *supra* notes 163–69 and accompanying text.

<sup>215</sup> See *infra* notes 252, 270, 299 and accompanying text.

### C. For the Market

Although traditional network markets tend to tip into a monopoly, some economists stress that competition works effectively in such markets.<sup>216</sup> These economists subscribe to the Schumpeterian view of market competition, named after Austrian economist Joseph Schumpeter.<sup>217</sup> According to Schumpeter, competition markets characterized by rapid technological innovation occur not *in* the market (to maximize market share) but *for* the entire market (to win ultimate market dominion).<sup>218</sup> This form of market competition “strikes not at the margins of the profits and outputs of the existing firms but at their foundations and their very lives.”<sup>219</sup> To that end, according to the Schumpeterian view, monopolists’ reigns will be short-lived even if a traditional network industry is monopolized.<sup>220</sup> Soon disruptive new technology will emerge to displace the old monopoly, and a new monopolist will rise under the old one. The second monopolist’s reign will also be short-lived, for the next generation of disrupters will displace it as well.<sup>221</sup> For this reason, competition for the market is also dubbed a “serial monopoly”<sup>222</sup> or simply “creative destruction.”<sup>223</sup>

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<sup>216</sup> See, e.g., David S. Evans & Richard Schmalensee, *Some Economic Aspects of Antitrust Analysis in Dynamically Competitive Industries*, 2 INNOVATION POL. & ECON. 1, 1 (2002).

<sup>217</sup> JOSEPH A. SCHUMPETER, CAPITALISM, SOCIALISM, AND DEMOCRACY 81–86 (Taylor & Francis 2003), <https://periferiaactiva.files.wordpress.com/2015/08/joseph-schumpeter-capitalism-socialism-and-democracy-2006.pdf> [<https://perma.cc/EVZ3-F3GV>]; Shapiro, *supra* note 213, at 368–69.

<sup>218</sup> SCHUMPETER, *supra* note 217. See also Besen & Farrell, *supra* note 179, at 120, 175 (contrasting competition from within markets).

<sup>219</sup> SCHUMPETER, *supra* note 217, at 84.

<sup>220</sup> See Evans & Schmalensee, *supra* note 216, at 14 (“[I]f dynamic competition is healthy, the presence of short-run market power is not a symptom of a market failure that will harm consumers.”); Richard Schmalensee, *Antitrust Issues in Schumpeterian Industries*, 90 AM. ECON. REV. PAPERS & PROC. 192, 193 (2000) (arguing that “[t]raditional tests for monopoly power do not measure . . . [the] fragility” of market dominance in the software industry); David J. Teece & Mary Coleman, *The Meaning of Monopoly: Antitrust Analysis in High-Technology Industries*, 43 ANTITRUST BULL. 801, 820–22 (1998).

<sup>221</sup> Some displaced network technologies include telegraphy, telecopying, and wire-telephony.

<sup>222</sup> See LIEBOWITZ & MARGOLIS, *supra* note 48, at 10.

<sup>223</sup> See SCHUMPETER, *supra* note 217, at 83.

Some economists believe that creative destruction aptly describes the evolution of technology in the late 20th century.<sup>224</sup> Only five of the twenty American companies with the largest market capitalization at the end of 1985 made the same list in 2000.<sup>225</sup> Specifically, AT&T, the second-most valuable company in 1970 and the fourth-most valuable in 1985, was not among these survivors.<sup>226</sup> Traditional network effects drive creative destruction because the sustainable market dominance that they facilitate provides strong incentives for potential disruptive innovators to try their luck.<sup>227</sup> As Andy Grove, the former CEO of Intel, aptly observed, in this environment, “only the paranoid survive.”<sup>228</sup>

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<sup>224</sup> But not all economists believe this. Some economists push back against the Schumpeterian vision by invoking the theory of technological “lock-in.” According to this premise, users may find it difficult to switch away from an incumbent system either because of the high costs associated with having to learn a new system or because of the sunk and unrecoverable costs that were invested in the old system. See Lemley, *supra* note 69, at 1050 (discussing “resource commitments”); Carl Shapiro, *Exclusivity in Network Industries*, 7 GEO. MASON L. REV. 673, 675 (1999); Peter S. Menell, *An Analysis of the Scope of Copyright Protection for Application Programs*, 41 STAN. L. REV. 1045, 1066–71 (1989) (discusses learning costs). Both difficulties are bolstered by the collective action problem that emerges because a significant number of users must switch together from the old system to the new for the latter to become a viable alternative. See Lemley & McGowan, *Legal Implications*, *supra* note 44, at 497; LIEBOWITZ & MARGOLIS, *supra* note 48, at 19 (discussing the collective action problem). Thus, the higher the switching costs, and the larger the incumbent’s installed user base, the more difficult it becomes for creative destruction to occur. See Liebowitz & Margolis, *Network Externality*, *supra* note 44, at 134 (“[N]etwork externalities are asserted to constitute market failure.”); Farrell & Saloner, *supra* note 52, at 71–72 (calling this result “excess inertia”). The most commonly cited example of an innovation impeding lock-in is the longlisting persistence of the QWERTY typewriter keyboard in the face of allegedly superior alternatives. See Paul A. David, *Clio and the Economics of QWERTY*, 75 AM. ECON. REV. 332, 335–36 (1985). The problem of lock-in may be especially severe in the context of UGD networks in the absence of standardization and portability regimes that reduce at least some of the costs associated with switching (overcoming the collective action problem is harder). See, e.g., Uri Y. Hacoen, *Policy Implications of User-Generated-Data Network Effects*, 33 FORDHAM INTELL. PROP. MEDIA & ENT. L.J. 340, 399–400 (2023).

<sup>225</sup> See Evans & Schmalensee, *supra* note 216, at 3–4.

<sup>226</sup> See *id.*

<sup>227</sup> To disrupt the incumbent’s monopoly, a creative disruptor must overcome the network-effects driven technological lock-in. See generally Evans & Schmalensee, *supra* note 216; Shelanski & Sidak, *supra* note 44, at 9.

<sup>228</sup> See generally ANDREW S. GROVE, ONLY THE PARANOID SURVIVE (1996). Grove’s statement can be read in two ways. An optimist will read Grove to imply that Schumpeterian economists are right, that competition forces will keep network

Yet even if one believes in the disruptive power of creative destruction in traditional network industries, there are reasons to doubt this conviction in the presence of UGD network effects. Under usual circumstances, creative destruction emerges from complementary products to the primary monopolized good that has the potential to mature into a disruptive substitute.<sup>229</sup> Accordingly, in *United States v. Microsoft Corp.*, the government's main concern was that Microsoft attempted to extend its operating system monopoly into the complementary browser and middleware markets to prevent these markets from maturing into viable substitutes that could threaten Microsoft's primary monopoly.<sup>230</sup> Nevertheless, as explained in the previous section, competition across markets in the presence of UGD network effects leads entire sectors in the consumer economy to tip in favor of a few multi-industry conglomerates. This dissipation of competition across markets leaves little room for creative disruptors to emerge.<sup>231</sup>

Since UGD is essential for data-driven innovation, unless the incumbent data platforms share their troves of UGD with their nascent competitors, the latter will be far less capable of innovating than the

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monopolists in check, and that the fears of technological lock-in, as discussed in *supra* note 224 and accompanying text, are overestimated. See Richard A. Posner, *Natural Monopoly and Its Regulation*, 21 STAN. L. REV. 548, 558 (1969) ("A monopolist maximizing long-run profit may . . . decide to sell at a somewhat lower price in order to discourage entry by potential competitors . . ."); Lemley & McGowan, *Legal Implications*, *supra* note 44, at 529; Richard J. Gilbert & Michael L. Katz, *An Economist's Guide to U.S. v. Microsoft*, 15 J. ECON. PERSP. 25, 29 (2001); William J. Baumol, *Contestable Markets: An Uprising in the Theory of Industry Structure*, 72 AM. ECON. REV. 1, 1–3 (1982). A pessimist can read Grove's "paranoia" sentiment to imply that even aggressive anticompetitive strategies to kill early creative destructors will also aid the incumbent monopolists' survival. See *infra* notes 252, 270, 299 and accompanying text.

<sup>229</sup> See Farrell & Weiser, *supra* note 197, at 111 (explaining complementors are in the best position to disrupt incumbent network monopolists); see also Timothy F. Bresnahan, *A Remedy That Falls Short of Restoring Competition*, ANTITRUST, Fall 2001, at 67, <https://web.stanford.edu/~tbres/research/anti-bre.pdf> [<https://perma.cc/ZX4Z-AAMC>].

<sup>230</sup> See Farrell & Weiser, *supra* note 197, at 110–11 (explaining complementary applications could evolve into substitutes); Bresnahan, *supra* note 229; Michael D. Whinston, *Exclusivity and Tying in United States v. Microsoft: What We Know, and Don't Know*, 15 J. ECON. PERSP. 63, 73 (2001); Shelanski & Sidak, *supra* note 44, at 60.

<sup>231</sup> The question of whether this trend is positive or negative depends on whether the integration across markets was done to utilize UGD-driven (or other) efficiencies or for illegitimate anticompetitive reasons such as "killing competition." This question is difficult to assess. See *infra* notes 252, 270, 299 and accompanying text.

former.<sup>232</sup> Of course, this does not mean that nascent competitors could not develop innovations superior to the incumbent. However, it does mean that such competitors might struggle to bring these innovations to maturation without aid from the incumbents or access to their UGD networks.<sup>233</sup> In other words, it is far likelier that the incumbent data platforms will absorb their nascent competitors—or copy their technology without legal or technical barriers—than it is that the nascent competitors disrupt and displace the incumbent data platforms independently.<sup>234</sup> The resulting implications for welfare dynamics are intricate. UGD-driven monopolies can be innovation powerhouses, but they can also utilize their power in a way that is socially concerning.<sup>235</sup> The next Part explores how.

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<sup>232</sup> See Viktor Mayer-Schönberger & Thomas Ramge, *A Big Choice for Big Tech*, FOREIGN AFFS. (Aug. 13, 2018), <https://www.foreignaffairs.com/articles/world/2018-08-13/big-choice-big-tech> [<https://perma.cc/PM3Z-M7GV>] (“More and more, the success of a firm rests on its ability to use the information it possesses.”).

<sup>233</sup> See DIG. COMPETITION, *supra* note 18, at 4; see also STUCKE & GRUNES, *supra* note 18, at 201. However, nascent competitors’ companies could still offer products that are superior in other dimensions such as privacy or security.

<sup>234</sup> See Lops et al., *supra* note 130, at 6 (“Google is far, far more likely to purchase a start-up with valuable search technology (something it tends to do twice a month) than it is to be displaced by one.”); DIG. COMPETITION, *supra* note 18, at 48; Cockburn et al., *supra* note 119, at 4 (“As the competitive advantage of incumbents is reinforced, the power of new entrants to drive technological change may be weakened.”).

<sup>235</sup> See Varian, *Recent Trends*, *supra* note 17, at 820 (“[C]ritics argue that ‘internet giants’ are ‘squashing’ young firms by acquiring them, thereby preventing them from reaching their full potential. But a different interpretation of acquisitions is that they are a prerequisite for small firms to achieve their full potential—they are ‘more profitable as part of a larger organization that enables them to scale up quickly and efficiently.’”) (quoting Kathleen M. Kahle & René M. Stulz, *Is the US Public Corporation in Trouble?*, J. ECON. PERSP., Summer 2017, at 85); CRÉMER ET AL., *supra* note 18, at 117–18 (“Frequently, the project of the bought up start-up is integrated into the ‘ecosystem’ of the acquirer or into one of their existing products. Such acquisitions are different from killer acquisitions as the integration of innovative complementary services often has a plausible efficiency rationale.”). *But see infra* notes 252, 270, 299 and accompanying text.

### III. COUNTERVAILING EFFECTS

*The worst enemy of life, freedom and the common decencies is total anarchy; their second worst enemy is total efficiency.*<sup>236</sup>

*Aldous Huxley*

As explained in Part II, market competition dynamics are becoming less stable considering UGD network effects, while market concentration and conglomeration are becoming more natural and more defensible against disruption. Economic theory is usually suspicious of concentrated and uncontestable market power.<sup>237</sup> The fear is that without disciplinary competitive pressures, monopolists—even natural ones—will attempt to raise prices, limit output, and stagnate innovation.<sup>238</sup> UGD network effects may challenge this concern. Because the consumers of UGD-driven products provide the raw material needed for product production, data platforms are incentivized to enhance consumption, which usually leads to keeping prices low and output plentiful.<sup>239</sup> Furthermore, data platforms

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<sup>236</sup> See STEVEN SCALET, *MARKETS, ETHICS, AND BUSINESS ETHICS* ch. 6 (2d ed. 2018); Gary Blair, *Why We Fascinate and Focus on Total Efficiency*, MEDIUM (June 28, 2020), <https://gazblair.medium.com/why-we-fascinate-and-focus-on-total-efficiency-99d2f327b9aa> [<https://perma.cc/4RMR-LETF>].

<sup>237</sup> U.S. competition policy does not demonize market power *per se*, but when the contestability of that market is impaired—for example because of lock-in monopolization theory—then some pro-competition measures are justified. See *supra* note 224 and accompanying text.

<sup>238</sup> See KARL E. CASE ET AL., *PRINCIPLES OF MICROECONOMICS* 316 (10th ed. 2012). For application for telecommunication, see STUART M. BENJAMIN ET AL., *TELECOMMUNICATIONS LAW AND POLICY* 614–18 (2001). Because market competition in traditional network industries is incapable of stopping network monopolists from realizing these harms, policymakers have traditionally sought to subject network monopolies to government regulation. See Katz & Shapiro, *Network Externalities*, *supra* note 44.

<sup>239</sup> See LEE, *supra* note 58, at 171 (“[T]he requirement in U.S. law that plaintiffs prove the monopoly is actually harming consumers. AI monopolists, by contrast, would likely be delivering better and better services at cheaper prices to consumers . . . .”); Rubinfeld & Gal, *Access Barriers*, *supra* note 92, at 375 (“[I]t is these very barriers which create an incentive for firms to compete over the provision of products or services from which they can get access to such information, sometimes even providing them free of charge.”); Ford, *supra* note 19, at 1576 (“The genius of this system is that it will be absolutely free to the consumer.”); LERNER, *supra* note 92, at 4; see also CRÉMER ET AL., *supra* note 18, at 88; MOORE & TAMBINI, *supra* note 95, at 28; Adam Davidson, *A Washing Machine That Tells*



become more capable of improving their existing products and innovating new ones as those existing products become more accessible and usable.<sup>240</sup>

Nevertheless, UGD-driven market concentration is not concern-free.<sup>241</sup> Once inter-market tipping occurs, the incumbent data platforms no longer face competitive pressures from within and across markets. These platforms are more likely to hinder (rather than cultivate) UGD-driven innovation and to engage in UGD-driven price discrimination and behavioral manipulation.

Worse, data platforms might hinder innovation and engage in price discrimination and behavioral manipulation even before inter-market tipping naturally occurs through the realization of UGD-driven efficiencies. Data platforms might leverage UGD-driven intelligence to pursue these welfare-reducing ends as exclusionary instruments designed to achieve “unnatural” inter-market tipping. The following sections explore these countervailing effects in detail.

#### A. Innovation Hindrance

As explained in Part II, UGD-driven conglomerates are likely to be more efficient innovators than many of their nascent competitors.<sup>242</sup> Nevertheless, given the reduction in competitive market pressures, incumbent data platform (and competitor) incentives to

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*the Future*, NEW YORKER (Oct. 16, 2017), <https://www.newyorker.com/magazine/2017/10/23/a-washing-machine-that-tells-the-future> [<https://perma.cc/EXH7-7JWV>] (stating that the best way to expand market share is “to push prices as low as possible”); Matt McFarland, *Your Car’s Data May Soon Be More Valuable Than the Car Itself*, CNN: BUSINESS (Feb. 7, 2017), <http://money.cnn.com/2017/02/07/technology/car-data-value/index.html> [<https://perma.cc/53JL-CQCV>].

<sup>240</sup> See *supra* Part I.

<sup>241</sup> See generally Stucke, *supra* note 81 (outlining concerns about data-opolies).

<sup>242</sup> See Peter Thiel, *Competition is for Losers*, WALL ST. J., (Sept. 12, 2014), <https://www.wsj.com/articles/peter-thiel-competition-is-for-losers-1410535536> [<https://perma.cc/2W38-TEP6>] (“Creative monopolies aren’t just good for the rest of society; they’re powerful engines for making it better.”); cf. Hal R. Varian, *Economic Scene; If There Was a New Economy, Why Wasn’t There a New Economics?*, N.Y. TIMES (Jan. 17, 2002) <https://www.nytimes.com/2002/01/17/business/economic-scene-if-there-was-a-new-economy-why-wasn-t-there-a-new-economics.html> [<https://perma.cc/63P9-NPBW>] (suggesting that the new economy makes megacorporations more efficient).

continue innovating are likely to diminish. As Jens Prüfer and Christoph Schottmüller explain,

An important feature of a tipped market is that there are very little incentives for both the dominant firm and the ousted firm to further invest in innovation. The reason is that, in the stable steady state where one firm has virtually no demand and the other firm has virtually full demand, the ousted firm knows that the dominant firm offers consumers both a significantly higher quality level and has significantly lower marginal costs of innovation, due to its larger stock of user information. The latter characteristic enables the dominant firm to match any innovative activities of the ousted firm at lower marginal innovation cost and hence keep its quality advantage . . . . [T]he smaller firm gives up innovating if its quality lags behind the larger firm's too much. Knowing this, the dominant firm's best response is to also save on investing in innovation—and still reap the monopoly profit.<sup>243</sup>

Nascent competitors may still innovate to disrupt and displace the incumbent data platforms in hope of being acquired by them.<sup>244</sup> Venkatesh Rao suggests that nascent competitors may increasingly become outsourced research and development stations where innovations are absorbed into features of existing products rather than standalone products.<sup>245</sup> Yet even this promising startup-empowering vision may end up distorting innovation progress. For instance, prospective innovators (and their investors) may soon learn that they will gain the most significant payoffs by developing innovations that complement the *status quo* favored by the incumbent data platforms

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<sup>243</sup> Prüfer & Schottmüller, *supra* note 73, at 968.

<sup>244</sup> See Mark Huberty, *Awaiting the Second Big Data Revolution: From Digital Noise to Value Creation*, 15 J. INDUS. COMPETITION & TRADE 35, 46 (2015); DIG. COMPETITION, *supra* note 18, at 49; D. Daniel Sokol, *Vertical Mergers and Entrepreneurial Exit*, 70 FLA. L. REV. 1357, 1366 (2018) (discussing the motivations for exit).

<sup>245</sup> Venkatesh Rao, *Entrepreneurs Are the New Labor: Part I*, FORBES (Sept. 3, 2012) <https://www.forbes.com/sites/venkateshrao/2012/09/03/entrepreneurs-are-the-new-labor-part-i/> [https://perma.cc/6T7G-XDJS].

instead of trying to disrupt it.<sup>246</sup> Worse, the incumbent data platforms may acquire emerging competitors to hinder their innovations, especially if the expected maturation of these innovations does not sit well with the data platforms' other business objectives.<sup>247</sup>

The concern of strategically hindering technological innovation exists in traditional network effect markets but is heightened in the presence of UGD network effects. In such an environment, the incumbent data platforms can use UGD-driven analytics to surveil competitors, predict market trends, and identify nascent competitive risks in real-time.<sup>248</sup> Commenters have dubbed this phenomenon “nowcasting.”<sup>249</sup> For instance, Meta has used the UGD-analytics application Onavo and other user-facing analytics services to extract valuable intelligence about competing services' success and ingenuity.<sup>250</sup> Based on these insights, Meta made strategic business decisions, such as imitating Meerkat and Periscope's successful live-video feature in 2016 or acquiring WhatsApp in 2014.<sup>251</sup>

Crucially, nowcasting allows the incumbent data platforms to hinder innovation even before inter-market tipping occurs. Nowcasting creates a negative feedback loop that mirrors the positive

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<sup>246</sup> See, e.g., DIG. COMPETITION, *supra* note 18, at 50; Khan, *supra* note 41, at 978–79 (explaining how the dominant data platforms impact venture capital).

<sup>247</sup> See Colleen Cunningham et al., Killer Acquisitions 1 (Apr. 22, 2020), <https://ssrn.com/abstract=3241707> [<https://perma.cc/Z52N-L8SD>]; STIGLER FINAL REPORT, *supra* note 18, at 75 (“Incumbents have the incentive and ability to stand in the way of possibly disruptive innovation.”); Lim, *supra* note 159, at 55; see also CRÉMER ET AL., *supra* note 18, at 121; Jones & Tonetti, *supra* note 160, at 2819; Steven Davidoff Solomon, *New Buying Strategy as Facebook and Google Transform into Web Conglomerates*, N.Y. TIMES, (Aug. 5, 2014), <https://dealbook.nytimes.com/2014/08/05/new-strategy-as-tech-giants-transform-into-conglomerates/> [<https://perma.cc/WWP4-SRKV>].

<sup>248</sup> See STIGLER FINAL REPORT, *supra* note 18, at 71; Khan, *supra* note 41, at 977–78.

<sup>249</sup> See McIntosh, *supra* note 18, at 193.

<sup>250</sup> See Betsy Morris & Deepa Seetharaman, *The New Copycats: How Facebook Squashes Competition From Startups*, WALL ST. J. (Aug. 9, 2017), <https://www.wsj.com/articles/the-new-copycats-how-facebook-squashes-competition-from-startups-1502293444> [<https://perma.cc/GFB8-6KNK>]; see also Josh Constone, *Facebook Pays Teens to Install VPN That Spies on Them*, TECHCRUNCH (Jan. 30, 2019) <https://social.techcrunch.com/2019/01/29/facebook-project-atlas/> [<https://perma.cc/YB2W-5FLZ>].

<sup>251</sup> See Jon Fingas, *Facebook Knew about Snap's Struggles Months Before the Public*, ENGADGET (Aug. 13, 2017), <https://www.engadget.com/2017-08-13-facebook-knew-about-snap-struggles-through-app-tracking.html> [<https://perma.cc/FV78-VK24>].

feedback loop described in Part I: the more user data platforms have, and the more data they generate, the better the data platforms become at nowcasting (namely identifying and neutralizing competitive risks in real-time). As the data platforms become more apt nowcasters, the less threatened and the more capable, resourceful, and motivated they become to improve their nowcasting capabilities even further. Similarly, data platforms may profit from expanding across markets, as explained in Part II, without utilizing UGD-driven efficiencies if, by doing so, they become better nowcasters.<sup>252</sup>

### B. Price Discrimination

Incumbent data platforms can use UGD-driven intelligence not only to surveil their competitors, but also to discriminate among their users in price and quality.<sup>253</sup> Economists define price discrimination as charging different prices to different consumers for the same goods based on the maximum price each consumer is willing to pay.<sup>254</sup> To price discriminate effectively, businesses need to understand consumers, which requires them to collect and analyze

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<sup>252</sup> See Farrell & Weiser, *supra* note 197, at 107 (explaining the incentive to prevent disruption may lead to anticompetitive leverage across markets); *supra* notes 227–28 and accompanying text.

<sup>253</sup> See Ramsi A. Woodcock, *Big Data, Price Discrimination, and Antitrust*, 68 HASTINGS L.J. 1371, 1385 (2017); Aziz Z. Huq, *The Public Trust in Data*, 110 GEO. L.J. 333, 356 (2021) (“[D]ata can be used to enable first-degree price discrimination by which different consumers are presented with variable, individualized prices for the same product); Alessandro Acquisti, Curtis Taylor & Liad Wagman, *The Economics of Privacy*, 54 J. ECON. LIT. 442, 466 (2016); Ryan Calo & Alex Rosenblat, *The Taking Economy: Uber, Information, and Power*, 117 COLUM. L. REV. 1623, 1659 (2017) (discussing first-degree price discrimination in the ride-sharing context). While this Section’s analysis focuses on price, the same dynamics apply to quality.

<sup>254</sup> See Alexandra Twin, *What is Price Discrimination, and How Does It Work?* INVESTOPEDIA (June 13, 2022), [https://www.investopedia.com/terms/p/price\\_discrimination.asp#:~:text=Price%20discrimination%20is%20a%20selling,the%20customer%20to%20agree%20to.](https://www.investopedia.com/terms/p/price_discrimination.asp#:~:text=Price%20discrimination%20is%20a%20selling,the%20customer%20to%20agree%20to.) [https://perma.cc/7RPE-AVCK]. The technical definition of “price discrimination” is earning different rates of return on units of the same product, meaning that the difference between unit cost and price is different for different units. See HERBERT HOVENKAMP, *FEDERAL ANTITRUST POLICY: THE LAW OF COMPETITION AND ITS PRACTICE* 621 (2011). By contrast, economists call charging different prices to different consumers “differential pricing.” *Id.*

UGD.<sup>255</sup> For instance, since the dawn of higher education, colleges successfully price discriminate with student tuition rates by deciphering candidates' willingness and ability to pay based on their financial aid information.<sup>256</sup> Airline companies also successfully discriminate with ticket prices by evaluating their travelers' ability and willingness to pay based on purchase timing and travel itinerary information.<sup>257</sup> Thus, given their growing access to UGD and improved analytics capabilities, data platforms can perfect their price discrimination schemes like never before.<sup>258</sup>

The welfare implications of perfect price discrimination (also known as first-degree price discrimination or personalized pricing) are ambiguous.<sup>259</sup> By forcing consumers to pay a price equal to the value they place on each good, perfect price discrimination not only broadens the range of transactions executed, but also deprives consumers of the entire surplus of their transactions, leaving them no better off than if they had not transacted at all.<sup>260</sup> Worse, perfect

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<sup>255</sup> See Hal R. Varian, *Price Discrimination*, in HANDBOOK OF INDUSTRIAL ORGANIZATION 597, 604 (R. Schmalensee & R.D. Willig eds., 1989); Woodcock, *supra* note 253. Other conditions required for price discrimination are sufficient market power to allow the seller to set prices above marginal costs and limitations on the ability of consumer arbitrage.

<sup>256</sup> See ANNA BERNASEK & D.T. MONGAN, *ALL YOU CAN PAY* 67–73 (2015).

<sup>257</sup> See RICHARD H.K. VIETOR, *CONTRIVED COMPETITION: REGULATION AND DEREGULATION IN AMERICA* 69, 72–73 (1996); Robert G. Cross et al., *Milestones in the Application of Analytical Pricing and Revenue Management*, 10 J. REVENUE & PRICING MGMT. 8, 9–10 (2011).

<sup>258</sup> See Woodcock, *supra* note 253, at 1385; Newman, *supra* note 73, at 445; cf. Monopolies Commission, *supra* note 147. UGD network effects are expected to empower price discrimination because the process of UGD-driven product refinement and personalization helps to keep users within information “filter bubbles.” It also prevents them from conducting post-sale arbitrage, which would undermine the success of the price discrimination scheme. See Stucke & Ezrachi, *How Digital Assistants*, *supra* note 175, at 1272.

<sup>259</sup> See GIOVANNI SARTOR, *PANEL FOR THE FUTURE OF SCIENCE AND TECHNOLOGY, THE IMPACT OF THE GENERAL DATA PROTECTION REGULATION (GDPR) ON ARTIFICIAL INTELLIGENCE*, EUROPEAN PARLIAMENTARY RESEARCH SERVICE 29 (June 2020), [https://www.europarl.europa.eu/thinktank/en/document/EPRS\\_STU\(2020\)641530](https://www.europarl.europa.eu/thinktank/en/document/EPRS_STU(2020)641530) [<https://perma.cc/BLU3-6TCY>] (stating that price discrimination is not only unfair, it also undermines the efficiency of the economy); Matthew A. Edwards, *Price and Prejudice: The Case Against Consumer Equality in the Information Age*, 10 LEWIS & CLARK L. REV. 559, 592 (2006) (discussing perfect price discrimination and efficient outputs).

<sup>260</sup> See HAL R. VARIAN, *INTERMEDIATE MICROECONOMICS: A MODERN APPROACH*, 446, 463–65, 480–81 (2006); Woodcock, *supra* note 253, at 1381; Ramsi A. Woodcock,

price discrimination often inflicts the heaviest burden on vulnerable consumers, those unaware that price discrimination is occurring, or those who cannot negotiate or switch to better deals.<sup>261</sup> In 2012, the Wall Street Journal reported that several major companies, including Staples and Home Depot, systematically used information about users' physical location to display different online prices to different consumers.<sup>262</sup> The report found that the retailers targeted the worst deals to the lowest-income populations, which had fewer retail outlets in their locations to compete with the online stores.<sup>263</sup> A similar study showed that online prices for The Princeton Review's SAT tutoring packages are higher for consumers in areas with large Asian populations.<sup>264</sup> Perfect price discrimination is also ethically

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*Personalized Pricing as Monopolization*, 51 CONN. L. REV. 311, 315 (2019); MAS-COLELL ET AL., MICROECONOMIC THEORY 386–87 (Oxford Univ. Press 1995); Curtis R. Taylor, *Consumer Privacy and the Market for Customer Information*, 35 RAND. J. ECON. 631, 643 (2004); Oren Bar-Gill, *Algorithmic Price Discrimination When Demand Is A Function of Both Preferences and (Mis)perceptions*, 86 U. CHI. L. REV. 217, 220–21 (2019).

<sup>261</sup> See Nathan Newman, *How Big Data Enables Economic Harm to Low-Income Consumers*, HUFFPOST (Nov. 15, 2014), [https://www.huffpost.com/entry/how-big-data-enables-econ\\_b\\_5820202](https://www.huffpost.com/entry/how-big-data-enables-econ_b_5820202) [<https://perma.cc/AUG4-7JFZ>]; Newman, *supra* note 73, at 445; Huq, *supra* note 253, at 367 (“Populations that are economically or socially marginal, in contrast, will not benefit from personal data’s absent public interventions.”); Morgan Wild & Marini Thorne, *A Price of One’s Own: An Investigation into Personalised Pricing in Essential Markets*, CITIZENS ADVICE (Aug. 31, 2018), <https://www.citizensadvice.org.uk/about-us/our-work/policy/policy-research-topics/consumer-policy-research/consumer-policy-research/a-price-of-ones-own-an-investigation-into-personalised-pricing-in-essential-markets/> [<https://perma.cc/5RHU-TCJY>] (“Personalised pricing could make things worse for vulnerable consumers.”); Gal & Rubinfeld, *supra* note 18, at 755; FED. TRADE COMM’N, *BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION? UNDERSTANDING THE ISSUES* 9–11 (2016), <https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf> [<https://perma.cc/X25T-ZQ8L>] (outlining ways in which the use of big data can generate harmful consequences for low-income groups); Shelanski, *supra* note 83, at 1680.

<sup>262</sup> Jennifer Valentino-DeVries et al., *Websites Vary Prices, Deals Based on Users’ Information*, WALL ST. J. (Dec. 24, 2012), <https://www.wsj.com/articles/SB1000142412788732377204578189391813881534> [<https://perma.cc/2MZF-7JBD>].

<sup>263</sup> *Id.*

<sup>264</sup> See Julia Angwin et al., *The Tiger Mom Tax: Asians Are Nearly Twice as Likely to Get a Higher Price from Princeton Review*, PROPUBLICA (Sept. 1, 2015), <https://www.propublica.org/article/asians-nearly-twice-as-likely-to-get-higher-price-from-princeton-review> [<https://perma.cc/UX8N-HN9U>]; Jeff Larson et al., *Unintended*

controversial because it enables businesses to adjust prices based on parameters that many people may consider arbitrary or unjust.<sup>265</sup> As Sandra Wachter explains,

Inferential analytics widens the range of victims of discriminatory actions. These new types of victims do not map to or might not correlate with current concepts in the law. New types of discrimination become possible, for example less favourable treatment can be given for people who own dogs . . . [because] groups such as “dog owners” are not protected under nondiscrimination law . . . [I]t can still seem “unreasonable,” counterintuitive, or unjust to use dog ownership as a deciding factor for loan applications, despite it being lawful to use the characteristic as a basis for decision-making.<sup>266</sup>

These unjust criteria are particularly concerning in cases where they are indicative of users’ hurdles, biases, or specific vulnerabilities.<sup>267</sup> In other words, price discrimination may be economically perfect (mirroring actual user demand) yet can be socially and morally degrading. For instance, the European Data Protection Working Party has recently raised concerns about online game developers’ ability to use price discrimination to target children who are cognitively susceptible to overspending on gaming.<sup>268</sup> Similarly, Uber

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*Consequences of Geographic Targeting*, TECH. SCI. (Aug. 31, 2015), <https://techscience.org/a/2015090103/> [<https://perma.cc/E4ES-N5XU>].

<sup>265</sup> See Calo & Rosenblat, *supra* note 253, at 1647.

<sup>266</sup> Sandra Wachter, *Affinity Profiling and Discrimination by Association in Online Behavioural Advertising*, 35 BERKELEY TECH. L.J. 1, 56–58 (2020).

<sup>267</sup> See John Bohannon, *Facebook Preferences Predict Personality Traits*, SCI. MAG. (Mar. 11, 2013), <https://www.sciencemag.org/news/2013/03/facebook-preferences-predict-personality-traits> [<https://perma.cc/LLY2-FN XR>] (“People’s likes also predicted far more sensitive personal attributes such as homosexuality, religion, political party membership, and even use of cigarettes, alcohol, and drugs . . . .”); AMNESTY INT’L, *supra* note 18, at 37 (arguing that UGD-driven profiling enables data platforms to target vulnerable populations); Ian Sample, *One Facebook ‘Like’ Is All It Takes to Target Adverts, Academics Find*, GUARDIAN (Nov. 13, 2017), <https://www.theguardian.com/science/2017/nov/13/facebook-likes-targeted-advertising-psychological-persuasion-academics-research> [<https://perma.cc/3SCX-E4BL>].

<sup>268</sup> See Article 29 Data Protection Working Party, *Guidelines on Automated Individual Decision-making and Profiling for the Purposes of Regulation 2016/679*, at 26, WP 251

executives recently admitted that the company could charge higher prices for users in vulnerable positions, such as riders carpooling late at night or riders whose phone battery is running low.<sup>269</sup>

Lastly, price discrimination also has indirect welfare-reducing effects. Similar to the pathology of nowcasting discussed above, price discrimination creates a negative feedback loop that mirrors the positive feedback loop described in Part I: the more users data platforms have, and the more data they generate, the better the data platforms become at price discriminating among their users. As data platforms become more apt price discriminators, the more capable, resourceful, and motivated they become to improve their price discrimination capabilities further. In other words, data platforms may expand across markets, as explained in Part III, even without utilizing UGD-driven efficiencies if doing so allows them to become better price discriminators.<sup>270</sup> Thus, price discrimination may harm consumers irrespective of the welfare implication of the price discrimination practice itself by excluding more efficient innovators or price competitors from adjacent markets.<sup>271</sup>

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17/EN (Oct. 3, 2017), <https://ec.europa.eu/newsroom/article29/items/612053/en> [<https://perma.cc/B4WA-83U3>]; see also COMPETITION & MKTS. AUTH., THE COMMERCIAL USE OF CONSUMER DATA: REPORT ON THE CMA'S CALL FOR INFORMATION 154 (2015), [https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment\\_data/file/435817/The\\_commercial\\_use\\_of\\_consumer\\_data.pdf](https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/435817/The_commercial_use_of_consumer_data.pdf) [<https://perma.cc/S9KT-65E6>]; Hoofnagle & Whittington, *supra* note 149, at 613–14; Nicole Kobie, *The Complicated Truth About China's Social Credit System*, WIRED UK (June 7, 2019) <https://www.wired.co.uk/article/china-social-credit-system-explained> [<https://perma.cc/7HBL-UTMC>].

<sup>269</sup> See Biz Carson, *You're More Likely to Order a Pricey Uber Ride if Your Phone Is About to Die*, BUS. INSIDER (May 18, 2016), <https://www.businessinsider.in/Youre-more-likely-to-order-a-pricey-Uber-ride-if-your-phone-is-about-to-die/articleshow/52317846.cms> [<https://perma.cc/F4WQ-2AYT>] (explaining that, in studying its consumers, the Uber data-science team discovered that people whose phone batteries are low are more willing to pay inflated or “surge” pricing—leading to concerns that the company is interested in what amounts to contextual or individualized price-gauging); Haugh et al., *supra* note 101, at 621–22.

<sup>270</sup> See Farrell & Weiser, *supra* note 197, at 107 (explaining that the incentive to prevent disruption may lead to anticompetitive leverage across markets).

<sup>271</sup> See *id.* at 103–04.



### C. Behavioral Manipulation

With sufficient UGD-driven intelligence, incumbent data platforms could move beyond price discrimination to the more disturbing practice of “behavioral manipulation.”<sup>272</sup> Behavioral manipulation occurs when instead of manipulating product prices to align with predetermined user preferences, data platforms manipulate users’ behavior, and possibly even preferences, to align with the data platforms’ policy objectives.<sup>273</sup> Behavioral manipulation is not a

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<sup>272</sup> Cf. Ariel Porat, *Changing People’s Preferences by the State and the Law* 36 (University of Chicago, Pub. L. Working Paper No. 722, 2019) (discussing preference manipulation by the state).

<sup>273</sup> A similar label that has been applied to this pathology is “behavioral price discrimination.” See Ariel Ezrachi and Maurice E. Stucke, *Virtual Competition*, 7 J. EUR. COMPETITION L. & PRAC. 585, 585 (2016); Ezrachi & Stucke, *Digital Assistant Devious*, *supra* note 175, at 8. Others have applied the label “persuasion profiling.” See Maurits Kaptein & Dean Eckles, *Selecting Effective Means to Any End: Futures and Ethics of Persuasion Profiling*, in *PERSUASIVE TECHNOLOGY: LECTURE NOTES IN COMPUTER SCIENCE* 82, 82–93 (2010). However, these labels usually describe a more narrow type of preference manipulation that is only meant to increase users’ demand for products, services, or advertisements. As described below, preference manipulation can go beyond these examples. For a discussion on how preference manipulation can increase users’ demand, see Bar-Gill, *supra* note 260, at 220–21; Paul Heidhues & Botond Köszegi, *Naïveté-Based Discrimination*, 132 Q.J. ECON. 1019, 1020–21, 1026–27 (2017); Haugh et al., *supra* note 101, at 612; Chongwoo Choe & Noriaki Matsushima, *Behavior-Based Price Discrimination and Product Choice*, 58 REV. IND. ORG. 263, 263–73 (2021); Dirk Bergemann et al., *The Economics of Social Data*, RAND J. ECON. 1, 1–34 (2022); see also Tal Zarsky, *Online Privacy, Tailoring, and Persuasion*, in *PRIVACY AND TECHNOLOGIES OF IDENTITY: A CROSS-DISCIPLINARY CONVERSATION* Ch. 12 (2006); Ryan Calo, *Digital Market Manipulation*, 82 GEO. WASH. L. REV. 995, 1012–14 (2014); Daniel Susser et al., *Online Manipulation: Hidden Influences in a Digital World*, 4 GEO. L. TECH. REV. 1, 31 (2019); Karen Yeung, *Hypernudge: Big Data as a Mode of Regulation by Design*, 20 INFO., COMM’N & SOC’Y 118, 122 (2017); STIGLER FINAL REPORT, *supra* note 18, at 41–60; Stanley M. Besen, *Competition, Privacy, and Big Data*, 28 CATH. U. J.L. & TECH. 63, 77 (2020); Joshua A.T. Fairfield & Christoph Engel, *Privacy as a Public Good*, 65 DUKE L.J. 385, 429 (2015); Tim Wu, *Blind Spot: The Attention Economy and the Law*, 82 ANTITRUST L.J. 771, 784 (2019). Another similar concept is emotional manipulation. For this discussion, see SHOSHANA ZUBOFF, *THE AGE OF SURVEILLANCE CAPITALISM: THE FIGHT FOR A HUMAN FUTURE AT THE NEW FRONTIER OF POWER* 202 (2018) (describing developments in the field of emotional analytics and profiling); Sam Machkovech, *Report: Facebook Helped Advertisers Target Teens Who Feel “Worthless”*, ARS TECHNICA (May 1, 2017), <https://arstechnica.com/information-technology/2017/05/facebook-helped-advertisers-target-teens-who-feel-worthless/> [<https://perma.cc/DJ25-ZCQ2>] (noting that Facebook can identify and leverage users’ vulnerabilities); Sam Biddle, *Facebook Uses Artificial Intelligence to Predict Your Future Actions for Advertisers, Says Confidential Document*, INTERCEPT (Apr. 13, 2018), <https://theintercept.com/2018/04/13/facebook->

novel phenomenon.<sup>274</sup> Data platforms already engage in subtle behavioral manipulation to increase users' demand for products, services, or messages they advertise.<sup>275</sup> As Ariel Ezrachi and Maurice Stucke explain:

[F]irms harvest our personal data to identify which emotion (or bias) will prompt us to buy a product, and what's the most we are willing to pay. Sellers, in tracking us and collecting data about us, can tailor their advertising and marketing to target us at critical moments with the right price and emotional pitch. So behavioral discrimination increases profits by increasing overall consumption (by shifting the demand curve to the right and price discriminating) and reducing consumer surplus.<sup>276</sup>

By aggregating and analyzing UGD, data platforms create so-called "persuasion profiles," which are optimized and personalized to sway users' behavior based on collective and individual biases and vulnerabilities.<sup>277</sup> For decades, behavioral economists have known of collective psychological biases such as decoy choices,

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advertising-data-artificial-intelligence-ai/ <https://perma.cc/V38M-Y9RY>]; Robert Booth, *Facebook Reveals News Feed Experiment to Control Emotions*, GUARDIAN (June 29, 2014), <https://www.theguardian.com/technology/2014/jun/29/facebook-users-emotions-news-feeds> [<https://perma.cc/369J-S97K>].

<sup>274</sup> See, e.g., Wu Youyou et al., *Computer-based Personality Judgments Are More Accurate than Those Made by Humans*, 112 PROC. NAT'L ACAD. SCI. 1036, 1036 (2015). Accurate personality profiles were extracted from UGD, such as Facebook "Likes" and messages. See Bohannon, *supra* note 267; Andrew H. Schwartz et al., *Personality, Gender, and Age in the Language of Social Media: The Open-Vocabulary Approach*, 8 PLOS ONE 1, 1 (2013); Jennifer Golbeck et al., *Predicting Personality from Twitter*, 2011 IEEE INT'L CONFERENCE ON PRIVACY SEC. RISK & TR. TRUST 149, 149 (2011). They were also extracted from Flickr photos. See Cristina Segalin et al., *The Pictures We Like Are Our Image: Continuous Mapping of Favorite Pictures into Self-Assessed and Attributed Personality Traits*, 8 IEEE TRANS. ON AFFECTIVE COMPUT. 1, 16 (2017).

<sup>275</sup> See Sandra C. Matz et al., *Psychological Targeting as an Effective Approach to Digital Mass Persuasion*, 114 PROC. NAT'L ACAD. SCI. 12714, 12714 (2017) ("[T]argeting people with persuasive appeals tailored to their psychological profiles can be used to influence their behavior as measured by clicks and conversions."); Biddle, *supra* note 273; Zeke Faux, *How Facebook Helps Shady Advertisers Pollute the Internet*, BLOOMBERG (Mar. 27, 2018), <https://www.bloomberg.com/news/features/2018-03-27/ad-scammers-need-suckers-and-facebook-helps-find-them> [<https://perma.cc/PU3M-YKKL>].

<sup>276</sup> EZRACHI & STUCKE, PROMISE AND PERILS, *supra* note 175, at 101.

<sup>277</sup> *Supra* note 269 and accompanying text.

price steering, deliberate complexation, and framing effects.<sup>278</sup> Traditional marketers have leveraged these vulnerabilities with primitive forms of so-called “dark patterns”—such as using the \$9.99 price tag or locating the more expensive products at eye-level shelves—to manipulate consumers’ choices and encourage them to buy more products.<sup>279</sup> Yet the digital UGD-driven environment has dramatically enhanced the efficiency and opportunities for market manipulation.<sup>280</sup> As Ryan Calo explains,

When a company can design an environment from scratch, track consumer behavior in that environment, and change the conditions throughout that environment based on what the firm observes, the possibilities to manipulate are legion. Companies can reach consumers at their most vulnerable, nudge them into overconsumption, and charge each consumer the most she may be willing to pay.<sup>281</sup>

Using UGD analytics, data platforms can recognize and leverage the psychological, emotional, and social vulnerabilities of particular sub-populations (such as the disabled, elderly, or children) and of individual users.<sup>282</sup> Data platforms use these capabilities to nudge

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<sup>278</sup> See generally RICHARD H. THALER & CASS R. SUNSTEIN, *NUDGE: IMPROVING DECISIONS ABOUT HEALTH, WEALTH, AND HAPPINESS* (2008). While Thaler and Sunstein suggest use of nudge strategies to design policies that change consumers’ behavior to advance their own personal interests, behavioral manipulation, as discussed here, describes the use of such mechanisms to advance the data platforms interests, whether or not these interests are aligned with those of users.

<sup>279</sup> Jon D. Hanson & Douglas A. Kysar, *Taking Behavioralism Seriously: The Problem of Market Manipulation*, 74 N.Y.U. L. REV. 630, 635 (1999); Jon D. Hanson & Douglas A. Kysar, *Taking Behavioralism Seriously: Some Evidence of Market Manipulation*, 112 HARV. L. REV. 1420, 1427–28 (1999). “Dark Patterns” is a term that is used to describe the opposite of Thaler and Sunstein’s “nudge,” namely to steer users away from their best interests. See Jamie Luguri & Lior Jacob Strahilevitz, *Shining a Light on Dark Patterns*, 13 J.L. ANALYSIS 43, 44 (2021).

<sup>280</sup> See Calo, *supra* note 273, at 999; Susser et al., *supra* note 273, at 29; Tarleton Gillespie, *Platforms Are Not Intermediaries*, 2 GEO. L. TECH. REV. 198, 211 (2018); BRIAN JEFFREY FOGG, *PERSUASIVE TECHNOLOGY: USING COMPUTERS TO CHANGE WHAT WE THINK AND DO* 32 (2003).

<sup>281</sup> Calo & Rosenblat, *supra* note 253, at 1628.

<sup>282</sup> *Id.* at 1628, 1651 (“By tracking consumer habits in close detail, not only are firms in a position to exploit the general cognitive biases consumers share across a population, but they are also able to identify the specific and often highly idiosyncratic limitations of each

users toward overconsumption of the data platforms' products and services as well as increase user demand for third-party marketing messages.<sup>283</sup> Further, experts have found that data platforms such as Meta and Google use UGD-driven analytics to make their products and services addictive to encourage vulnerable users to engage in overconsumption.<sup>284</sup> Similarly, the personalized advertising tools

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consumer.”); Luguri & Strahilevitz, *supra* note 279, at 99; Sample, *supra* note 267 (noting personalization based on a single Facebook “Like” may boost consumers’ perception (measured by click-through rates) by 40% and actual sales by 50%); FED. TRADE COMM’N, BIG DATA, *supra* note 261, at 10; Nathan Newman, *How Big Data Enables Economic Harm to Consumers, Especially to Low-Income and Other Vulnerable Sectors of the Population*, 18 J. INTERNET 11, 12 (2014); FED. TRADE COMM’N, DATA BROKERS: A CALL FOR TRANSPARENCY AND ACCOUNTABILITY 31 (2014), <https://www.ftc.gov/system/files/documents/reports/data-brokers-call-transparency-accountability-report-federal-trade-commission-may-2014/140527databrokerreport.pdf> [<https://perma.cc/AJK4-WUTU>] (describing personality ‘scores ranks’); Till Speicher et al., *Potential for Discrimination in Online Targeted Advertising*, 81 PROC. MACH. LEARNING RSCH. 1, 1 (2018); Solon Barocas & Helen Nissenbaum, *Big Data’s End Run Around Anonymity and Consent*, in PRIVACY, BIG DATA, AND THE PUBLIC GOOD 44, 55 (2014) (explaining how big UGD-driven inferences reveal user vulnerabilities); Frances H. Montgomery et al., *Patterns: Big Brother or Promoting Mental Health?* 31 J. TECH. 61, 62 (Jan. 2013) (showing that UGD patterns are indicative of depression); Raghavendra Kotikalapudi et al., *Associating Internet Usage with Depressive Behavior Among College Students*, 31 IEEE TECH. & SOC’Y MAG. 73, 78–79 (2012).

<sup>283</sup> Indeed, because companies maximize profit through personal data extraction, they are incentivized to maximize (as opposed to optimize) users’ day-to-day engagement with the company’s products and services. This type of business dynamic is largely unprecedented in corporate history. See Stucke, *supra* note 81, at 310–11 (“[D]ata-opolies’, like Facebook and Google, even without significant rivals, can increase profits by increasing our engagement with their products. This distinguishes data-opolies from past monopolies.”); DATA-DRIVEN INNOVATION, *supra* note 16, at 12–13; AMNESTY INT’L, *supra* note 18, at 39. For the same reason, data platforms have incentive to nudge users away from competitors that might deflect UGD away from their platforms’ ecosystem. See Bourreau & de Streel, *supra* note 59, at 18.

<sup>284</sup> See Mattha Busby, *Social Media Copies Gambling Methods “To Create Psychological Cravings”*, GUARDIAN (May 8, 2018), <https://www.theguardian.com/technology/2018/may/08/social-media-copies-gambling-methods-to-create-psychological-cravings> [<https://perma.cc/33L7-T4W8>]; Henry Gray, *Social Media’s Use of Slot Machine Psychology Has Its Users Hooked, What Direction Does Big Tech Take Next?*, WE HEART (Apr. 22, 2021), <https://www.we-heart.com/2019/09/04/social-media-and-the-slot-machine/> [<https://perma.cc/94T6-B8NE>]; Charles Arthur, *It’s Time to Admit We Are Addicted to Facebook*, CNN (Nov. 16, 2018), <https://www.cnn.com/2018/11/16/opinions/facebook-addiction-zuckerberg-opinion-intl/index.html> [<https://perma.cc/2536-SCJF>]; Lina M. Khan & David E. Pozen, *A Skeptical View of Information Fiduciaries*, 133 HARV. L. REV. 498, 505 (2019) (“By and large, addictive user behavior is good for business.”); AMNESTY INT’L, *supra* note 18, at

that Google and Meta employ are alleged to successfully increase consumer demand for products and services,<sup>285</sup> brands (including

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29; see also COUNCIL OF EUROPE'S COMMITTEE OF MINISTERS, DECLARATION ON THE MANIPULATIVE CAPABILITIES OF ALGORITHMIC PROCESSES (Feb. 13, 2019), [https://search.coe.int/cm/pages/result\\_details.aspx?ObjectId=090000168092dd4b](https://search.coe.int/cm/pages/result_details.aspx?ObjectId=090000168092dd4b) [<https://perma.cc/L37Z-E2U4>]; Ian Leslie, *The Scientists Who Make Apps Addictive*, ECONOMIST (Oct. 20, 2016) <https://www.economist.com/1843/2016/10/20/the-scientists-who-make-apps-addictive> [<https://perma.cc/5S4A-VPV7>]; Patrick Berlinquette, *I Used Google Ads for Social Engineering. It Worked*, N.Y. TIMES (July 7, 2019) <https://www.nytimes.com/2019/07/07/opinion/google-ads.html> [<https://perma.cc/5TBE-GSLS>]; STIGLER FINAL REPORT, *supra* note 18, at 64; Srnicek, *supra* note 58; SUBCOMM., INVESTIGATION OF COMPETITION, *supra* note 18, at 50–53; Deepa Seetharaman, *Facebook Prods Users to Share a Bit More*, WALL ST. J. (Nov. 13, 2015) <https://www.wsj.com/articles/facebook-prods-users-to-share-a-bit-more-1446520723> [<https://perma.cc/VR8X-VM8T>] (explaining how Facebook nudges users to post content).

<sup>285</sup> See Edmund Lee, *What's the Best Strategy for Targeting Your Display Ads?*, AD AGE (Apr. 4, 2011), <https://adage.com/article/special-report-audience-buying-guide/strategy-targeting-display-ads/149661> [<https://perma.cc/LF5F-PV9J>] (“A retargeted display ad will encourage 1,000% more people to search for a product than a standard ad, according to the study.”); David Kirkpatrick, *Study: 71% of Consumers Prefer Personalized Ads*, MARKETING DIVE (May 9, 2016), <https://www.marketingdive.com/news/study-71-of-consumers-prefer-personalized-ads/418831/> [<https://perma.cc/2RT7-WHTJ>]; Rebecca Walker Reczek, et al., *Targeted Ads Don't Just Make You More Likely to Buy — They Can Change How You Think About Yourself*, HARV. BUS. REV. (Apr. 4, 2016), <https://hbr.org/2016/04/targeted-ads-dont-just-make-you-more-likely-to-buy-they-can-change-how-you-think-about-yourself> [<https://perma.cc/8H2Z-L9VE>].

the Facebook brand),<sup>286</sup> presidential candidates,<sup>287</sup> Coronavirus vaccinations,<sup>288</sup> and many more.<sup>289</sup>

Behavioral manipulation is harmful because the data platforms' and their users' interests are not necessarily aligned.<sup>290</sup> As commercial businesses, data platforms are incentivized to increase value for their shareholders, not to enhance user welfare and well-being.<sup>291</sup> By nudging users to overconsume their services or advertised promotions, data platforms optimize the former objective, not (and often at the expense of) the latter.<sup>292</sup> In addition to causing users to

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<sup>286</sup> See *Marketing Case Studies and Success Stories*, META FOR BUS., <https://en-gb.facebook.com/business/success> [<https://perma.cc/6X7R-Y69V>] (last visited Sept. 22, 2023) (displaying examples of boosting in the success of targeted marketing campaigns); Ryan Mac & Sheera Frenkel, *No More Apologies: Inside Facebook's Push to Defend Its Image*, N.Y. TIMES (Sept. 21, 2021), <https://www.nytimes.com/2021/09/21/technology/zuckerberg-facebook-project-amplify.html> [<https://perma.cc/L4U5-RCSU>].

<sup>287</sup> See OMR, *Alexander Nix: From Mad Men to Math Men*, YOUTUBE (Mar. 10, 2017), <https://www.youtube.com/watch?v=6bG5ps5KdDo&t=387s> [<https://perma.cc/UCP6-3HZ6>]; EXECUTIVE OFFICE OF THE PRESIDENT, PRESIDENT'S COUNCIL OF ADVISORS ON SCIENCE AND TECHNOLOGY, REPORT TO THE PRESIDENT, BIG DATA AND PRIVACY: A TECHNOLOGICAL PERSPECTIVE 29 (May 2014) [https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/PCAST/pcast\\_big\\_data\\_and\\_privacy\\_-\\_may\\_2014.pdf](https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/PCAST/pcast_big_data_and_privacy_-_may_2014.pdf) [<https://perma.cc/H2UV-FHRP>].

<sup>288</sup> See Jeremy B. Merrill & Drew Harwell, *Telling Conservatives It's a Shot to 'Restore Our Freedoms': How Online Ads Are Promoting Coronavirus Vaccination*, WASH. POST (Aug. 24, 2021), <https://www.washingtonpost.com/technology/2021/08/24/vaccine-ad-targeting-covid/> [<https://perma.cc/4PLG-G8UJ>].

<sup>289</sup> See Hoofnagle & Whittington, *supra* note 1449, at 630–31 (describing Facebook's monetization options).

<sup>290</sup> See generally ZUBOFF, *supra* note 273 (exploring the tension between users and profit-maximizing data platforms).

<sup>291</sup> See, e.g., Khan & Pozen, *supra* note 284, at 504 (explaining Jack Balkin's proposal to impose fiduciary duties on data platforms toward users will not work because of conflicts of interest); Sylvie Delacroix & Neil D. Lawrence, *Bottom-up Data Trusts: Disturbing the 'One Size Fits All' Approach to Data Governance*, 9 INT'L DATA PRIVACY L 236, 241 (2019) (same).

<sup>292</sup> See Sue Halpern, *Apologize Later*, N.Y. REV. (Jan. 17, 2019), <https://www.nybooks.com/articles/2019/01/17/facebook-apologize-later/> [<https://perma.cc/9T8B-K5R2>]; Emily Bell & Taylor Owen, *The Platform Press: How Silicon Valley Reengineered Journalism*, TOW. CTR. DIG. J. (Mar. 29, 2017), [https://www.cjr.org/tow\\_center\\_reports/platform-press-how-silicon-valley-reengineered-journalism.php](https://www.cjr.org/tow_center_reports/platform-press-how-silicon-valley-reengineered-journalism.php) [<https://perma.cc/9X5J-B9FT>]; Nicholas Thompson & Fred Vogelstein, *Inside the Two Years that Shook Facebook—and the World*, WIRED (Feb. 12, 2018), <https://www.wired.com/story/inside-facebook-mark-zuckerberg-2-years-of-hell> [<https://perma.cc/QG2D-ZD6Q>].

consume more than they intend,<sup>293</sup> the Center for Humane Technology has identified numerous ancillary harms associated with the overconsumption of data platforms' services.<sup>294</sup> These harms range from psychological addiction<sup>295</sup> and depression<sup>296</sup> to social tribalism<sup>297</sup> and extremism.<sup>298</sup>

Additionally, like price discrimination and nowcasting, behavioral manipulation may also indirectly negatively affect user welfare.<sup>299</sup> Because data platforms enhance their ability to manipulate users' behavior the more (and more diverse) UGD they have, data platforms may profitably expand across markets without utilizing UGD-driven efficiencies.<sup>300</sup> In such cases, along with direct negative welfare implications, behavioral manipulation also causes

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<sup>293</sup> See Bar-Gill, *supra* note 260, at 220–21 (exploring the welfare implications of misconceptions).

<sup>294</sup> See *Ledger of Harms*, CTR. HUM. TECH., <https://ledger.humanetech.com/> [<https://perma.cc/J6ZA-6YS4>] (last updated June 2021).

<sup>295</sup> See *supra* note 284 and accompanying text.

<sup>296</sup> See, e.g., JEAN M. TWENGE, IGEN: WHY TODAY'S SUPER-CONNECTED KIDS ARE GROWING UP LESS REBELLIOUS, MORE TOLERANT, LESS HAPPY—AND COMPLETELY UNPREPARED FOR ADULTHOOD 93–94 (2017).

<sup>297</sup> See, e.g., CLAIRE WARDLE & HOSSEIN DERAKHSHAN, INFORMATION DISORDER: TOWARD AN INTERDISCIPLINARY FRAMEWORK FOR RESEARCH AND POLICY MAKING 46 (2017), <https://edoc.coe.int/en/media/7495-information-disorder-toward-an-interdisciplinary-framework-for-research-and-policy-making.html>

[<https://perma.cc/NBZ5-KCLE>]; Jonathan Stray, *Defense Against the Dark Arts: Networked Propaganda and Counter-Propaganda*, JONATHAN STRAY (Feb. 24, 2017), <http://jonathanstray.com/networked-propaganda-and-counter-propaganda> [<https://perma.cc/V8JU-TMH5>].

<sup>298</sup> See, e.g., Steve Rathje et al., *Out-Group Animosity Drives Engagement on Social Media*, 118 PROC. NAT'L ACAD. SCI. 1, 1 (2021); Zeynep Tufekci, *YouTube, the Great Radicalizer*, N.Y. TIMES (Mar. 10, 2018), <https://www.nytimes.com/2018/03/10/opinion/sunday/youtube-politics-radical.html> [<https://perma.cc/HS8M-A4NS>]; Morgan Keith, *From Transphobia to Ted Kaczynski: How TikTok's Algorithm Enables Far-Right Self-Radicalization*, BUS. INSIDER (Dec. 12, 2021) <https://www.businessinsider.com/transphobia-ted-kaczynski-tiktok-algorithm-right-wing-self-radicalization-2021-11> [<https://perma.cc/NHT5-4U6P>].

<sup>299</sup> See Farrell & Weiser, *supra* note 197, at 107, 111; see also *supra* notes 248–55 and accompanying text.

<sup>300</sup> In particular, Facebook was heavily invested in research that proved its ability to leverage UGD to successfully manipulate users' emotions. See *supra* notes 273–74 and accompanying text.

indirect welfare harms by excluding efficient innovators or price competitors from the market.<sup>301</sup>

Lastly, although it is less discussed and often poorly understood, data platforms may manipulate users' behavior while pursuing policies that they genuinely believe enhance users' welfare rather than shareholder profits.<sup>302</sup> For example, to maintain a civilized speech environment or defend intellectual property rights, data platforms such as Meta and Google employ content moderation services, which typically require UGD-driven automation.<sup>303</sup> However, because some human-defined concepts, such as "hate speech" and

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<sup>301</sup> See Farrell & Weiser, *supra* note 197, at 107 (explaining that the incentive to prevent disruption may lead to anticompetitive leverage across markets).

<sup>302</sup> Data platforms may—and often do—attempt to manipulate their users' behaviors in pursuit of profit maximization. See ZUBOFF, *supra* note 273 (linking behavioral manipulation to capitalism); *supra* notes 273–74 and accompanying text. But data platform UGD-driven algorithms creates behavioral manipulation concerns that are deeper and analytically distinct from having commercial profit-maximization motives. See SHALEV-SHWARTZ & BEN-DAVID, *supra* note 60, at 20 (reviewing early experiments by the psychologist B.F. Skinner which showed how behavior can be conditioned by experience); Ford, *supra* note 19, at 1576 (explaining how algorithmic governance conditions autonomous choice); Michal Gal, *Algorithmic Challenges to Autonomous Choice*, 25 TELECOMM. & TECH. L. REV. 59, 63 (2018); Delacroix & Lawrence, *supra* note 291, at 238; Delacroix & Veale, *supra* note 67, at 6; CHENEY-LIPPOLD, *supra* note 136, at 17. Moreover, regardless of the inherent bias of algorithmic governance, there are non-inherent yet highly concerning biases that result from limitations in algorithmic design or access to high quality data. For examples of systematic discrimination in UGD-driven services, see Joy Buolamwini & Timnit Gebru, *Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification*, 81 PROC. MACH. LEARNING RSCH. 77, 77 (2018) (discussing discrimination in gender classification systems); U.S. GOV'T ACCOUNTABILITY OFF., GAO-20-522, FACIAL RECOGNITION TECHNOLOGY: PRIVACY AND ACCURACY ISSUES RELATED TO COMMERCIAL USES 24–26 (2020); Allison Koenecke et al., *Racial Disparities in Automated Speech Recognition*, 117 PROC. NAT'L. ACAD. SCI. 7684, 7684 (2020) (reviewing discrimination in speech recognition applications); Jieyu Zhao et al., *Men Also Like Shopping: Reducing Gender Bias Amplification Using Corpus-level Constraints*, in PROC. 2017 CONF. ON EMPIRICAL METHODS NAT. LANGUAGE PROCESSING 2979 (2017), <https://aclanthology.org/D17-1323.pdf> [<https://perma.cc/P6K3-Y8HL>] (examining discrimination in image search); Paresh Dave, *Fearful of Bias, Google Blocks Gender-Based Pronouns from New AI Tool*, REUTERS (Nov. 27, 2018), <https://www.reuters.com/article/us-alphabet-google-ai-gender/fearful-of-bias-google-blocks-gender-based-pronouns-from-new-ai-tool-idUSKCN1NW0EF> [<https://perma.cc/BAL9-L59F>] (analyzing discrimination in predictive text).

<sup>303</sup> See Robert Gorwa et al., *Algorithmic Content Moderation, Technical and Political Challenges in the Automation of Platform Governance*, 3 BIG DATA AND SOC'Y 1, 7–11 (2020).



“fair use,” are inherently ambiguous, the data platforms’ automated content moderation systems tend to systematically remove legitimate speech and non-infringing content.<sup>304</sup> In these cases, although the policies that the data platforms try to enforce are socially desirable, they inevitably manipulate users’ future behavior by undermining their incentives to speak freely and innovate.<sup>305</sup>

Relatedly, as explained in Part I.A, to improve the quality of their UGD-driven services, data platforms often need to “experiment” by directing at least some users to unknown and potentially suboptimal choices.<sup>306</sup> For instance, services such as OkCupid or Waze might require users to try unrated dating partners or navigation routes, respectively.<sup>307</sup> You may think you are getting the best

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<sup>304</sup> See *id.* at 10 (explaining the problems of over-enforcement). The question of whether automated systems are inherently inapt, rather than technologically constrained, to evaluate highly contextual and cultural-related concepts is highly debated. See, e.g., Erik Brynjolfsson & Andrew McAfee, *Will Humans Go the Way of Horses?: Labor in the Second Machine Age*, FOREIGN AFFS. (June 16, 2015) <https://www.foreignaffairs.com/articles/2015-06-16/will-humans-go-way-horses> [<https://perma.cc/JJ8V-7KKP>]. Nevertheless, even if the second option is the correct one, the scale and the disadvantages of human-centered moderation justify the employment of automatic tools. See generally Billy Perrigo, *Inside Facebook’s African Sweatshop*, TIME (Feb. 17, 2022), <https://time.com/6147458/facebook-africa-content-moderation-employee-treatment/> [<https://perma.cc/P75J-9CP3>] (describing the mental implications associated with human content moderating).

<sup>305</sup> See Sharon Bar-Ziv & Niva Elkin-Koren, *Behind the Scenes of Online Copyright Enforcement: Empirical Evidence on Notice & Takedown*, 50 CONN. L. REV. 339, 378–81 (2017) (explaining that biased enforcement undermines the goals of copyright law); Ashley Belanger, *Lawmakers Tell Facebook to Stop Deleting Abortion Posts for No Reason*, ARS TECHNICA (July 12, 2022), <https://arstechnica.com/tech-policy/2022/07/lawmakers-press-facebook-to-stop-randomly-deleting-abortion-posts/> [<https://perma.cc/UDC7-CN7N>] (raising concerns that over-censorship might undermine users’ motivation to “turn to online communities to discuss and find information about reproductive rights”). Commentators have rightfully argued that data platforms do not have the proper economic incentives to make sure their systems are adequately balanced. See, e.g., Matthew Sag, *Internet Safe Harbors and the Transformation of Copyright Law*, 93 NOTRE DAME L. REV. 499, 540–43, 554–60 (2017). Nevertheless, as explained *supra* note 304, even if their incentives would have been perfectly aligned with the social ideal, algorithmic enforcement would still have an inevitable nudging aspect. See Karni A. Chagal-Feferkorn & Niva Elkin-Koren, *Lex AI: Revisiting Private Ordering by Design*, 36 BERKELEY TECH. L.J. 101, 101 (2021).

<sup>306</sup> See discussion *supra* Part I.

<sup>307</sup> See BERNASEK & MONGAN, *supra* note 256, at 56–57 (discussing the OkCupid example); Calo & Rosenblat, *supra* note 253, at 1669 (discussing the Waze example); Chagal-Feferkorn & Elkin-Koren, *supra* note 305, at 120–21; see also Geert Martens, *What*

possible match or the most efficient route every time, but some of those instances are merely test balloons. While data platforms' underlying policy goals are collectively desirable, the individual users' behaviors are nevertheless manipulated.<sup>308</sup>

Lastly, whenever they engage in UGD-driven personalization, data platforms inevitably manipulate their users' behaviors by nudging their future "selves" in the direction of their past "selves."<sup>309</sup> Any recommendation system that data platforms employ, no matter how it is adjusted, has some manipulative flavor by directing users' otherwise "autonomous" decision-making.<sup>310</sup> Using books as an example, Richard Ford explains,

I am influenced by what I read. Therefore, in some sense I become a different person with different ideas and different tastes based on what I read. I become more introspective after reading *Catcher in the Rye* in 10th grade, liberal after reading Isaiah Berlin's *Four Essays on Liberty*, and more critical after reading Michel Foucault's *Discipline and Punish* in

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*if Waze Were Evil?*, LINKEDIN (Apr. 15, 2019), <https://www.linkedin.com/pulse/what-waze-were-evil-geert-martens/> [<https://perma.cc/DS9G-UXKH>].

<sup>308</sup> See also Alexandra Chouldechova & Aaron Roth, *A Snapshot of the Frontiers of Fairness in Machine Learning*, 63 COMM'NS ACM 82, 88 (2020) (describing the trade-off between exploration and exploitation); SARAH BIRD ET AL., *EXPLORING OR EXPLOITING? SOCIAL AND ETHICAL IMPLICATIONS OF AUTONOMOUS EXPERIMENTATION IN AI 3* (2016), <https://papers.ssrn.com/abstract=2846909> [<https://perma.cc/VS4Z-8UJX>] (noting that because of information asymmetries, autonomous experimentation systems are likely to target the most vulnerable users); Allison J.B. Chaney et al., *How Algorithmic Confounding in Recommendation Systems Increase Homogeneity and Decreases Utility*, ACM RecSys (Oct. 30, 2017), <https://arxiv.org/abs/1710.11214?context=cs> [<https://perma.cc/4LGS-3TAX>].

<sup>309</sup> See Delacroix & Lawrence, *supra* note 291, at 238 ("Never before has the self we aspire to be been constrained to such an extent by our past . . ."); CHENEY-LIPPOLD, *supra* note 136, at 17; Michal S. Gal & Daniel L. Rubinfeld, *The Hidden Costs of Free Goods: Implications for Antitrust Enforcement*, 80 ANTITRUST L.J. 521, 547 (2016) ("[W]e cannot rely on short-run consumer choice as a reflection of long-term consumer interests.").

<sup>310</sup> This problem is worse in systems that employ reinforcement-learning techniques. See generally DAVID SCOTT KRUEGER ET AL., *HIDDEN INCENTIVES FOR AUTO-INDUCED DISTRIBUTIONAL SHIFT* (2020); MICAH CARROLL ET AL., *ESTIMATING AND PENALIZING INDUCED PREFERENCE SHIFTS IN RECOMMENDER SYSTEMS* (2021); ATOOSA KASIRZADEH & CHARLES EVANS, *USER TAMPERING IN REINFORCEMENT LEARNING RECOMMENDER SYSTEMS* (2021); SEBASTIAN FARQUHAR, RYAN CAREY, & TOM EVERI, *PATH-SPECIFIC OBJECTIVES FOR SAFER AGENT INCENTIVES* (2022).

college. We are what we read. This is a pretty basic First Amendment idea, that's why we don't want the state to control where people can bury their noses. Now if the Web sites continually suggest new things for me to read and I accept their suggestions, it will influence my intellectual development, just as my college education did. The more I accept their choices, the more likely I am to like the next choice, because my tastes were influenced by the last selection. Over time, one could say that rather than the computer profile reflecting my tastes, I reflect its tastes.<sup>311</sup>

The problem with “inadvertent” behavioral manipulation is more profound than the typical conflict of interest issues associated with data platforms’ existence as profit-maximizing commercial entities. The mere fact that data platforms govern any aspect of a user’s behavior is a fundamental threat to that person’s liberty and agency.<sup>312</sup>

The problem of behavioral manipulation—whether intentional or inadvertent—will likely intensify as data platforms broaden their UGD and analytics horizons. As discussed in Part I.C, the growing access to UGD will gradually enable data platforms to venture into more complex and morally-charged issues.<sup>313</sup> For example, data

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<sup>311</sup> Ford, *supra* note 19, at 1577.

<sup>312</sup> See also JAMES WILLIAMS, *STAND OUT OF OUR LIGHT: FREEDOM AND RESISTANCE IN THE ATTENTION ECONOMY* 88 (2018) (arguing data platforms “threaten to frustrate one’s authorship of one’s own life”); CHENEY-LIPPOLD, *supra* note 136, at 19 (arguing that “‘datafied’ lives . . . increasingly define who we are and who we can be”); ZUBOFF, *supra* note 273, at 94 (arguing that data platforms’ extraction of UGD transforms users into “means to others’ ends”); BRETT FRISCHMANN & EVAN SELINGER, *RE-ENGINEERING HUMANITY* (2018) (warning that digitalization leads to human automation); Rebecca Walker Reczek et al., *Targeted Ads Don’t Just Make You More Likely to Buy—They Can Change How You Think About Yourself*, HARV. BUS. REV. (Apr. 4, 2016), <https://hbr.org/2016/04/targeted-ads-dont-just-make-you-more-likely-to-buy-they-can-change-how-you-think-about-yourself> [<https://perma.cc/R332-H5KZ>].

<sup>313</sup> Steven Johnson & Nikita Iziev, *A.I. Is Mastering Language. Should We Trust What It Says?*, N.Y. TIMES (Apr. 15, 2022), <https://www.nytimes.com/2022/04/15/magazine/ai-language.html> [<https://perma.cc/EUZ3-EDC6>] (noting that “society is not monolithic in its values”) (internal quotations omitted); NICK BOSTROM, *SUPERINTELLIGENCE: PATHS, DANGERS, STRATEGIES* 257 (2014).

platforms could provide general personal assistance to help users tutor children, set up a career path, choose political candidates, or find love.<sup>314</sup> While potentially “efficient” in the purely economic sense, delegating such fundamental decision-making power to recommender systems is in some ways ethically controversial and predatory to human autonomy.<sup>315</sup>

Additionally, future data platforms could pursue even broader social goals, including preventing the spread of pandemics, addressing global inequality, and striving for world peace. These strategic goals may require the data platforms to make decisions that could be welfare-enhancing at the species level while at the same time welfare-reducing at the community or individual level.<sup>316</sup> For instance, in an allegedly leaked video The Verge acquired, Google researchers explore an unsettling futuristic vision where the data platform could subconsciously persuade users to surrender missing pieces of UGD to “plug gaps in its knowledge.”<sup>317</sup> Over time, as the video explains, the data platform could develop a species-level understanding of human behavior, enabling it to modify individuals’ behavior in ways that would “initially” be user-driven but would soon seek to “reflect Google’s values as an organization.”<sup>318</sup>

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<sup>314</sup> See, e.g., Stucke & Ezrachi, *How Digital Assistants*, *supra* note 175. While Maurice Stucke & Ariel Ezrachi rightly explain that data platforms may have the undesirable incentive to nudge users’ decision-making to optimize their own business agendas, as explained here, even if the future personal assistant will be produced by a non-profit venture and would only seek to enhance its user’s welfare (what they call “virtuous assistants”), it is still problematic. The only way to mitigate the risk of the manipulative harm of automation is to empower users with a “governance interest” over these systems. See generally Hacoen, *supra* note 224.

<sup>315</sup> See *supra* note 175 and accompanying text; see also Gal, *supra* note 302, at 90 (“[T]here are spheres of life in which choosing is more important than arriving at the optimal outcome. For example, it might be ill-advised to use an algorithm to choose one’s partner, no matter how superior the algorithm’s ‘taste.’”).

<sup>316</sup> Cf. discussion *supra* Part III.

<sup>317</sup> See Vlad Savov, *Google’s Selfish Ledger Is an Unsettling Vision of Silicon Valley Social Engineering*, VERGE (May 17, 2018), <https://www.theverge.com/2018/5/17/17344250/google-x-selfish-ledger-video-data-privacy> [<https://perma.cc/2XCN-MPZS>].

<sup>318</sup> *Id.* See also The Verge, *Leaked Google Video: A Disturbing Concept to Reshape Humanity with Data*, YOUTUBE (May 18, 2018), <https://www.youtube.com/watch?v=EoBAIQjWoUQ> [<https://perma.cc/N95A-MEVZ>]. Allowing Google to set the course of human evolution is not only concerning because

## CONCLUSION

UGD network effects are a new and tremendously important force in the emerging digital economy. Data analytics and machine learning technologies enable data platforms to optimize, personalize, and continuously diversify their services by identifying data patterns and predicting future trends and unsatisfied user demand.<sup>319</sup> A positive feedback loop that mimics the logic of traditional network effects emerges: the more users utilize these platforms (and the more UGD they surrender in the process), the better and more diverse these platforms' services will become.<sup>320</sup> The more services these platforms can offer and the better they become, the more users and utilization they attract and the better and more diverse their services become.

Driven by these dynamics, competition in UGD-driven markets tends to be unstable and lead to market tipping and monopolization.<sup>321</sup> Unlike traditional network industries, tipping tendencies are not confined to specific identifiable markets but spread across "linkable" markets in a way that challenges classic antitrust market definitions.<sup>322</sup> So, while it is difficult to pinpoint why 1970s AT&T should be allowed to integrate into telephone manufacturing<sup>323</sup> or why 1980s Microsoft should be allowed to integrate into web browsing,<sup>324</sup> there are clear and convincing UGD-driven justifications for why Google's general search should be integrated into vertical

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Google is a for-profit organization, but because it is not a democracy. *See generally* Hacoen, *supra* note 224.

<sup>319</sup> *See* discussion *supra* Part I.

<sup>320</sup> *See* discussion *supra* Part I.

<sup>321</sup> *See* discussion *supra* Part II.

<sup>322</sup> *See* discussion *supra* Part II.; *see also* STUCKE & GRUNES, *supra* note 18, at 1 (noting UGD-driven mergers and acquisitions are on the rise); JAMES MANYIKA ET AL., BIG DATA: THE NEXT FRONTIER FOR INNOVATION, COMPETITION, AND PRODUCTIVITY 113 (2011), [https://www.mckinsey.com/~media/mckinsey/business%20functions/mckinsey%20digital/our%20insights/big%20data%20the%20next%20frontier%20for%20innovation/mgi\\_big\\_data\\_full\\_report.pdf](https://www.mckinsey.com/~media/mckinsey/business%20functions/mckinsey%20digital/our%20insights/big%20data%20the%20next%20frontier%20for%20innovation/mgi_big_data_full_report.pdf) [<https://perma.cc/6YU9-MVFQ>].

<sup>323</sup> *See supra* note 196 and accompanying text; *see also* Brennan, *supra* note 187, at 790 (arguing in favor of divestiture in the AT&T case)

<sup>324</sup> *See supra* note 230 and accompanying text; Farrell, *supra* note 48, at 207 (describing the logic of divestiture). *But see* Shelanski & Sidak, *supra* note 44, at 1 (arguing against divestiture in the Microsoft case).

search, Facebook into Facebook’s apps, and Amazon’s Alexa into “Alexa’s Skills.”<sup>325</sup>

While some have suggested differently,<sup>326</sup> UGD network effects provide good reasons for market integration.<sup>327</sup> For example, by integrating into the vertical “Shopping” search engine, Google can provide shopping recommendations based on users’ past orders, browsing and searching history, and location.<sup>328</sup> Google Shopping can also process its users’ shopping transactions by using the payment method saved on the users’ Google accounts, simplify the shopping experience by integrating it with Google’s Assistant, and even optimize its product listing and website interfaces to better fit its users’ aesthetic preferences.<sup>329</sup>

Nevertheless, the UGD network’s effects may also be socially harmful.<sup>330</sup> Data platforms may utilize UGD-driven intelligence not to realize welfare-enhancing efficiencies, but to detect and neutralize competitive threats, price discriminate among users, and manipulate user behavior.<sup>331</sup> These countervailing effects will reduce social welfare by stagnating innovation, eliminating consumer surplus, fostering overconsumption, and compromising user autonomy.<sup>332</sup>

While these dynamics create significant challenges for competition policy, they are not entirely unprecedented.<sup>333</sup> As explained in

<sup>325</sup> See Khan, *supra* note 41 (exploring these examples in detail).

<sup>326</sup> *Id.* at 980. See also DIG. COMPETITION, *supra* note 18, at 61.

<sup>327</sup> See discussion *supra* Part I.

<sup>328</sup> See Ginny Marvin, *Local Google Shopping PLAs And Local Storefronts Roll Out To Limited Set Of Retailers*, SEARCH ENGINE LAND (Oct. 7, 2013), <https://searchengineland.com/local-google-shopping-plas-and-local-storefronts-roll-out-in-beta-173701> [<https://perma.cc/H57B-NGKC>].

<sup>329</sup> See Greg Sterling, *Google Brings Personalized Shopping, Local Inventory and Better Checkout to U.S.*, SEARCH ENGINE LAND (May 14, 2019), <https://searchengineland.com/google-bringing-new-shopping-experience-with-personalization-local-and-better-checkout-to-u-s-next-316976> [<https://perma.cc/R8FT-NL2J>]; cf. *supra* notes 211–12 and accompanying text (exploring the efficiencies of WeChat’s multi-app integration).

<sup>330</sup> See discussion *supra* Part III.

<sup>331</sup> See Farrell & Weiser, *supra* note 197, at 107, 111; see also *supra* notes 253, 274 and accompanying text.

<sup>332</sup> See Farrell & Weiser, *supra* note 197, at 107.

<sup>333</sup> Still, UGD network effects do introduce some novel policy challenges. Traditional network effects are usually concerned with positive network externalities whereas UGD

this Article, traditional network effect industries provide an essential and valuable benchmark for policymakers to examine. Centuries of telecommunications regulation provide important lessons for regulators and competition authorities to follow. For example, the Telecommunications Act of 1996 was the first law to compel incumbent telephone companies to unbundle their networks and provide interconnection to competitors on a reasonable and nondiscriminatory basis.<sup>334</sup>

Policymakers could mimic these existing arrangements by compelling incumbent data platforms to share UGD with competitors.<sup>335</sup> A complete analysis of the public policy implications of UGD network effects is conducted elsewhere and will not be repeated here.<sup>336</sup> The preceding analysis should serve as a cautionary tale to policymakers that call for instituting aggressive antitrust enforcement and even “breaking” Big Tech’s monopoly.<sup>337</sup> As this article has shown, where UGD-driven networks are concerned, the solution should not be breaking, but building—possibly even coupled with open access responsibilities and other principles of network governance.

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network effects involve positive and negative externalities. For a discussion on how these new challenges justify creative policy interventions, see Hacoen, *supra* note 224.

<sup>334</sup> See Telecommunications Act of 1996, Pub. L. No. 104, 110 Stat. 56 (1996) (codified as amended in scattered sections of 47 U.S.C.); 47 U.S.C. §§ 251(c)(2)–(3) (2000); see also Daniel F. Spulber & Christopher S. Yoo, *Access to Networks: Economic and Constitutional Connections*, 88 CORNELL L. REV. 885, 889–90 (2003).

<sup>335</sup> This applicability assumes that UGD serves as a barrier to competitive market entry. See Rubinfeld & Gal, *Access Barriers*, *supra* note 92; Bourreau & de Streel, *supra* note 59, at 11 (“[D]ata may constitute an essential component for product innovation. We might then be concerned that through the control of this essential component, a dominant firm may be able to foreclose competition.”); DIG. COMPETITION, *supra* note 18, at 74; SYMONS & BASS, *supra* note 11, at 25. Nevertheless, this assumption is not uncontested. See, e.g., Anja Lambrecht & Catherine E. Tucker, *Can Big Data Protect A Firm From Competition?*, COMPETITION POL’Y INT’L (Jan. 17, 2017), <https://www.competitionpolicyinternational.com/can-big-data-protect-a-firm-from-competition/> [https://perma.cc/VZT4-859F].

<sup>336</sup> See generally Hacoen, *supra* note 224.

<sup>337</sup> See *supra* note 41 and accompanying text.