

THE ROLE OF “BIG DATA” IN ONLINE PLATFORM COMPETITION

Andres V. Lerner¹

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I. Introduction

1. The collection of user data by providers of online services such as Facebook, Microsoft, Yahoo!, Apple, Amazon, and Google recently has become a popular topic in debates about the application of competition policy to online markets.² At issue is whether the collection of large amounts of data—sometimes referred to as “big data”—and in particular, data collected from users, can lead to markets “tipping” to dominant online platforms and, as a result, whether such markets merit earlier and more aggressive antitrust intervention.³

2. Arguments that the potential for the collection of user data to create insurmountable entry barriers are based on the assumption that online providers need a large base of users from whom to collect data, and large amounts of user data in order to offer valuable services and compete effectively for users. This “feedback loop” is presumed to lead to significant economies of scale and to the entrenchment of dominant platforms in markets for online services.⁴ Proponents of greater antitrust intervention in online markets claim that “big data,” particularly data from users, is the “oil” of the new online economy, and that this essential input is increasingly controlled by a handful of dominant players.⁵ In turn, it is argued that because dominant online platforms face insufficient competitive constraints, they are likely to collect more and more data from each user, and more sensitive personal data, and/or to undercompensate users for the value of the data they contribute—*i.e.*, provide insufficient services for free relative to the value of user data collected.

² See, *e.g.*, Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, NYU Information Law Institute. Nathan Newman is the Microsoft Research Fellow of the Information Law Institute at New York University, last revised August 14, 2014. See also, “Privacy and competitiveness in the age of big data: The interplay between data protection, competition law and consumer protection in the Digital Economy,” Preliminary Opinion of the European Data Protection Supervisor, March 2014, available at https://secure.edps.europa.eu/EDPSWEB/webdav/site/mySite/shared/Documents/Consultation/Opinions/2014/14-03-26_competition_law_big_data_EN.pdf.

³ See, *e.g.*, Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, NYU Information Law Institute, last revised August 14, 2014, p. 6: “depending on the market to correct monopoly dominance in such sectors is a poor strategy and why government intervention is needed, and needed at an earlier point than conventionally understood.”

⁴ The European Data Protection Supervisor stated that “[t]he collection and control of massive amounts of personal data are a source of market power for the biggest players in the global market for internet services.” (“Privacy and competitiveness in the age of big data,” European Data Protection Supervisor - EDPS/2014/06, March 26, 2014, available at http://europa.eu/rapid/press-release_EDPS-14-6_en.htm?locale=en.)

⁵ Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, NYU Information Law Institute, last revised August 14, 2014, pp. 3-4: “The rise of ‘big data’ as it’s sometimes labeled means that control of information, deemed the ‘new oil’ of the information economy, is skewed towards a few players with both the concentrated data processing power and supply of user data to dominate a particular sector.”

Senator Al Franken summarized this position, stating that “when companies become so dominant that they can violate their users’ privacy without worrying about market pressure, all that’s left is the incentive to get more and more information about you.”⁶ On the advertiser side, it is asserted that the collection of large volumes of user data, and the utilization of such data to target advertisements to users, leads to higher advertising rates, which are passed on to consumers in higher prices for goods and services.

3. In this article, I explore assumptions behind calls for greater antitrust scrutiny of the collection of user data by online platforms, and proposals for more aggressive antitrust intervention in such markets. The primary conclusion is that claims that collection of user data creates significant economies of scale, and thereby leads to the entrenchment of dominant online platforms, are unsupported by real-world evidence. Naked assertions regarding the role of user data in online platform competition regrettably have replaced a careful and meaningful analysis of competition in online markets.

4. User data is a valuable input into the provision of online services. Online providers collect user data in order to improve the services offered to users, and to monetize those services effectively through targeted advertising, which leads to valuable services being offered to users at subsidized prices, often for free. As a result, the collection of user data by online providers is an important part of the competitive process and generates sizable consumer benefits. Because of these competitive benefits, virtually all online providers collect data from users (from tracking user activity on their own sites, “data brokers,” and various other sources) in order to improve and monetize their services. The collection and use of customer data is commonplace not only for online firms, but for traditional offline (“brick-and-mortar”) businesses. The collection of user data is conducted by firms of all sizes, by firms offering a wide array of services to users, and by both new entrants and established players.

5. Although the collection of user data is generally valuable for online providers, the conclusion that such benefits of user data lead to significant returns to scale and to the entrenchment of dominant online platforms is based on unsupported assumptions. Although, in theory, control of an “essential” input can lead to the exclusion of rivals, a careful analysis of

⁶ Al Franken, “How Privacy Has Become an Antitrust Issue,” Huffington Post, March 30, 2012, available at http://www.huffingtonpost.com/al-franken/how-privacy-has-become-an_b_1392580.html.

real-world evidence indicates that such concerns are unwarranted for many online businesses that have been the focus of the “big data” debate.

6. As an initial matter, no single firm controls all, most, or even a significant amount of user data. Many online providers have access to significant amounts of user data from various sources, as the FTC has recognized.⁷ And, in contrast to economic theories about foreclosure of rivals through the control of an essential input, incumbent online providers do not have explicit or *de facto* exclusivity over user data. There are no exclusive contracts with users, and no pricing structure or features that lock-in users to a particular platform. As a result, users can, and often do, utilize multiple online services, even for the same type of task (referred to as user “multi-homing”), which gives multiple providers the ability to collect data on the same user. User data also is “non-rivalrous,” meaning that collection and use by one provider does not detract from collection and use by others. User multi-homing, and the non-rivalrous nature of user data, further diminish the possibility of any *de facto* exclusivity over user data.

7. Moreover, competitive success is not dictated by control over vast troves of data. The success of online providers is not driven by how much user data it can collect. Competition between online platforms is not unidimensional—the firm with the most data does not necessarily win. The quality of services offered to users, as well as the ability to monetize effectively by attracting advertisers, is driven by many other inputs including, perhaps most importantly, engineering resources and technological investments and innovation. There are many sources of data other than users, many other types of inputs into providing high-quality services, various dimensions of quality, and diverse means of competing for market share that do not involve user or other data. Neither does the collection of user data create insurmountable scale economies. In the provision of many online services, as in most businesses, there are economies of scale. But these economies are subject to rapidly diminishing returns, meaning

⁷ The Federal Trade Commission, in its statement closing its investigation of Google’s acquisition of DoubleClick in 2007, stated that “[t]he evidence indicates that neither the data available to Google ... constitutes an essential input to a successful online advertising product. A number of Google’s competitors have at their disposal valuable stores of data not available to Google. For instance, Google’s most significant competitors in the ad intermediation market, Microsoft, Yahoo!, and Time Warner have access to their own unique data stores. These firms own popular search engines, and will have access to consumer information from their internal ad servers, ad intermediation services, other web properties, and software.... All of these firms are vertically integrated, and all appear to be well-positioned to compete vigorously against Google in this new marketplace.” (Statement of Federal Trade Commission Concerning Google/DoubleClick, FTC File No. 071-0170, December 20, 2007, pp. 12-13, available at http://www.ftc.gov/system/files/documents/public_statements/418081/071220googledc-commstmt.pdf.)

that any advantages of scale weaken or even disappear at a low level. For all these reasons, it is highly unlikely that incumbent online providers could exclude rivals through the collection of user data.

8. Consistent with these economic characteristics of online markets, there is no evidence that the vast majority of online markets have “tipped” to dominant platforms. Contrary to claims regarding entrenchment of dominant platforms, the relatively short history of the Internet is filled with examples of large online providers thought to be dominant that subsequently were displaced by new entrants. This history illustrates that success can be temporary, and even seemingly unassailable incumbents can be quickly replaced by firms that offer better products or services. Multiple online platforms with unique services, technologies, and business models continue to competitively challenge each other, and it is uncertain which will be successful over the long term. The claimed propensity of online platforms to tip to dominant platforms is further diminished by the fact that online platforms are highly differentiated, and online markets are characterized by innovation and rapid technological change.

9. It is argued that cross-platform network effects between users and advertisers reinforce the tipping to and entrenchment of dominant platforms. However, these claims also are based on theoretical assumptions and not on facts. Although advertisers value the ability to access users, user demand for a platform is not substantially driven by the availability of advertisements. The fact that cross-platform network effects are essentially one-sided fundamentally weakens or eliminates the possibility of a feedback loop that locks users and advertisers to a dominant platform. If a smaller rival or new entrant offers a better service to users, network effects do not inhibit users from switching and, once users switch, advertisers likely would follow. Moreover, network effects for advertisers are diminished by per-click or per-impression pricing structure implemented by most online platforms, by very low costs for advertisers to place ads on multiple platforms (*i.e.*, multi-home), and through advertiser “congestion.” Consistent with these economic principles, there is significant multi-homing by both users and advertisers.

10. The overall conclusion is that calls for antitrust intervention related to the data collection efforts by online platforms are misplaced. Antitrust intervention in markets characterized by innovation and rapid technological change is often a questionable proposition, but it is especially so when concerns are based on unsupported assumptions rather than fact-based inquiry.

11. This paper is organized as follows. Section II discusses the competitive role of the collection of user data, and the widespread collection of user data by both online and offline firms. Section III addresses claims that the collection of user data leads to the entrenchment of dominant online platforms. Section IV discusses the empirical evidence that online markets have not tipped to dominant platforms, and the lack of cross-platform network effects that have been claimed to reinforce such tipping. Section V provides concluding comments.

II. The Collection of User Data by Online Providers is a Common and Important Part of the Competitive Process

A. The collection of customer data is widespread

1. The collection of user data by online providers

12. Virtually all online providers track user activity on their sites and collect demographic, behavioral, and other data from users. The collection of user data is conducted by firms of all sizes, by firms offering a wide array of services to users, and by both new entrants and established players. As I discuss in Section II.B., online providers collect this data in order to improve the quality of their services, and to monetize those services effectively through targeted advertising.

13. Various kinds of information generally are collected when users visit Internet websites, including technological data automatically collected without user input (*e.g.*, IP addresses and device identifiers), personal data (*e.g.*, user name, address/geographic location, gender, occupation, and personal interests), and behavioral data (*i.e.*, data on user online activities, such frequency of visits to a website and online purchases). The collection of many types of user data by online providers is typically accomplished through the use web “cookies,” which are essentially digital “ID tags.”⁸ Virtually all online providers, and many third-parties, use web

⁸ See, *e.g.*, Internet Advertising Bureau, “Understanding and Managing Cookies, Why They’re Used,” available at <https://www.iab.net/privacymatters/4.php>. According to a recent Congressional report, cookies are the “primary method for achieving online data sharing” by third-parties such as data brokers. (“A Review of the Data Broker Industry: Collection, Use and Sale of Consumer Data for Marketing Purposes,” Staff Report for Chairman Rockefeller, United States Senate Committee on Commerce, Science, and Transportation, December 18, 2013, p. 31.) With new Internet technologies and the proliferation of wireless Internet-connected devices, cookies are becoming increasingly unreliable for tracking users. Other technologies, such as pixel tags used in combination with “cookies,” or anonymous identifiers used on mobile devices where cookie technology is not available, are used to track various types of user information. (See, Internet Advertising Bureau, “Privacy and Tracking in the Post-Cookie World,” January 2014, available at <http://www.iab.net/media/file/IABPostCookieWhitepaper.pdf>.)

cookies to collect information from online users. For instance, a recent “Web Privacy Census” conducted by Berkeley Law School to analyze the prevalence of tracking cookies found that 98 percent of the 1,000 most popular websites had cookies or other tracking technology placed by the website itself or by a third-party, such as providers of advertising or marketing services that collect and analyze user data.⁹

14. With the growth of wireless smartphone and tablet devices that allow for accurate tracking of user location, the collection of user locational data also has become common.¹⁰ Location information is collected and used by many different online providers in order to improve the services offered to users and to target ads. For instance, “local search” apps like Yelp! may show recommendations for restaurants near the user, or provide point-to-point driving directions and traffic alerts. Netflix collects and utilizes user location data to show content recommendations to users based on preferences of other users in a similar geographic location. Companies such as Pandora and the Weather Channel collect location data from users of their app, and sell the data to advertising agencies, which may use this data, for example, to provide advertisements that are targeted based on the location of the users (*e.g.*, users that are near a retailer’s location).¹¹

15. Third-party firms, such as data brokers and advertising agencies, are increasingly involved in the collection of user data. Data brokers obtain consumer data from a variety of sources, both online and offline, including through arrangements with website owners allowing the broker to implement tracking technologies (such as cookies) on the website.¹² Data brokers

⁹ Chris Jay Hoofnagle & Nathan Good, “The Web Privacy Census,” Berkeley Law, University of California, October 2012, available at <http://www.law.berkeley.edu/privacycensus.htm>.

¹⁰ While the IP address of desktop computers can provide general information about a user’s location, mobile devices are equipped with global positioning systems (GPS) and/or Wi-Fi, which can be used to “geo-locate” a user with a high degree of accuracy. (See, *e.g.*, Kevin Tofel, “How much better is GPS over Wi-Fi positioning? Yelp knows,” GigaOM, August 17, 2012, available at <http://gigaom.com/2012/08/17/how-much-better-is-gps-over-wi-fi-positioning-yelp-knows/>.)

¹¹ Elizabeth Dwoskin, “In Digital Ads, It’s Location, Location, Location,” The Wall Street Journal, January 6, 2014, available at <http://blogs.wsj.com/digits/2014/01/06/in-digital-ads-its-location-location-location/>.

¹² One large data broker stated “there are over 250,000 websites who state in their privacy policy that they share data with other companies for marketing and/or risk mitigation purposes.” (“A Review of the Data Broker Industry: Collection, Use and Sale of Consumer Data for Marketing Purposes,” Staff Report for Chairman Rockefeller, United States Senate Committee on Commerce, Science, and Transportation, December 18, 2013, p. 20.) According to a recent Congressional report, “data brokers primarily obtain consumer data through five major avenues: government records and other public data; purchase or license from other data collectors; cooperative agreements with other companies; self-report by consumers, often through surveys, questionnaires, and sweepstakes; and social media.”

provide a variety of data collection, ad targeting, and demographic marketing services to clients, which may include large online providers like Facebook, small websites, and brick-and-mortar firms.¹³

2. *The collection of customer data by offline firms*

16. The collection of user data is commonplace not just by online firms, but also by traditional offline (“brick-and-mortar”) firms of all types and sizes. Brick-and-mortar firms collect data from customers in various ways, including public records, data purchased from third-party brokers, retailer loyalty cards, credit/debit card payments, and retailer receipts.¹⁴

17. The collection of data from customers serves a similar purpose for offline firms as it does for online providers. For instance, the collection and analysis of user data helps retailers target customers who are most likely to purchase their products.¹⁵ Retailers also use data collected from customers to improve their products, product placement, and store locations.¹⁶

(“A Review of the Data Broker Industry: Collection, Use and Sale of Consumer Data for Marketing Purposes,” Staff Report for Chairman Rockefeller, United States Senate Committee on Commerce, Science, and Transportation, December 18, 2013, p. 15.)

¹³ A 2012 article in *The Atlantic* described how the author identified 105 different companies that were collecting data about her online activities during a 36-hour period. Although the list included large, well-known firms such as Microsoft, Facebook, and Google, most of these firms were “smaller data and advertising businesses.” (Alexis Madrigal, “I’m Being Followed: How Google—and 104 Other Companies—Are Tracking Me on the Web,” *The Atlantic*, February 29, 2012, available at <http://www.theatlantic.com/technology/archive/2012/02/im-being-followed-how-google-151-and-104-other-companies-151-are-tracking-me-on-the-web/253758/>.)

¹⁴ Donna Ferguson, “How supermarkets get your data – and what they do with it,” *The Guardian*, June 7, 2013, available at <http://www.theguardian.com/money/2013/jun/08/supermarkets-get-your-data>; Charles Duhigg, “How Companies Learn Your Secrets,” *The New York Times*, February 16, 2012, available at <http://www.nytimes.com/2012/02/19/magazine/shopping-habits.html?pagewanted=all>.

¹⁵ See, e.g., Charles Duhigg, “How Companies Learn Your Secrets,” *The New York Times*, February 16, 2012, available at <http://www.nytimes.com/2012/02/19/magazine/shopping-habits.html?pagewanted=all>, describing how Target used data collected from customers and purchased from third-party providers to predict whether a customer is pregnant, in order to target coupons “timed to very specific stages of her pregnancy.” The article notes that Target collected data on customers from various sources, including purchasing data about “ethnicity, job history, the magazines you read, if you’ve ever declared bankruptcy or got divorced, the year you bought (or lost) your house, where you went to college, what kinds of topics you talk about online, whether you prefer certain brands of coffee, paper towels, cereal or apple sauce, your political leanings, reading habits, charitable giving and the number of cars you own.” The article notes that the “desire to collect information on customers is not new for Target or any other large retailer, of course. For decades, Target has collected vast amounts of data on every person who regularly walks into one of its stores.”

¹⁶ For example, a supermarket chain used “‘aggregated and anonymised data’ about shoppers’ Visa card transactions to help it decide on new store locations.” (Donna Ferguson, “How supermarkets get your data – and what they do with it,” *The Guardian*, June 7, 2013, available at <http://www.theguardian.com/money/2013/jun/08/supermarkets-get-your-data>.)

18. Like online firms, brick-and-mortar firms collect user location data. Some brick-and-mortar retailers track customer movements with user location data accessed through a customer's Wi-Fi-connected smartphone, which automatically connects to sensors placed in stores.¹⁷ Customer traffic data includes information such as foot-traffic patterns, number of customers entering a store, and how many minutes a customer spends in each aisle before proceeding to the point of sale.¹⁸ Retail stores also monitor customer movements and location by means of in-store video cameras, which follow visitors from entry to point-of-sale.¹⁹ Retail stores use this data to develop "heat maps" that indicate which areas of the store get the most traffic and thus determine effective product placement. Retailers also are able to use this information to staff stores more effectively, and thus provide better customer service.

B. Procompetitive rationales for the collection of user data by online providers

19. The widespread collection of customer data by firms of all types and sizes indicates that there are important procompetitive reasons for the collection of user data by online providers. As I explain in this section, online providers collect user data in order to improve the services they offer users and to monetize those services effectively, which leads to valuable services being offered to users at subsidized prices, often for free. Because of these benefits, the collection of user data is important, if not necessary, for most online providers to compete effectively with rivals.

1. User data allows online providers to improve the quality of services

20. Online providers utilize data collected from users to improve their services in several ways. Search providers, including general search engines (*e.g.*, Google, Bing, Yahoo!), specialized search sites (*e.g.*, Amazon), and other providers of search services (*e.g.*, job search

¹⁷ Elizabeth Dwoskin, "What Secrets Your Phone Is Sharing About You," *The Wall Street Journal*, January 13, 2014, available at <http://online.wsj.com/news/articles/SB10001424052702303453004579290632128929194>; Kristin Caliendo, "Your Smartphone Is Telling Your Secrets," *MoneyNews*, January 15, 2014, available at <http://www.moneynews.com/Personal-Finance/smartphone-Wi-Fi-Turnstyle-location/2014/01/15/id/547202/>.

¹⁸ Stephanie Clifford & Quentin Hardy, "Attention, Shoppers: Store Is Tracking Your Cell," *The New York Times*, July 14, 2013, available at http://www.nytimes.com/2013/07/15/business/attention-shopper-stores-are-tracking-your-cell.html?pagewanted=all&_r=0.

¹⁹ Tom Groenfeldt, "E-Commerce Style Big Data Analysis Meet Brick and Mortar Retailers," *Forbes*, August 3, 2012, available at <http://www.forbes.com/sites/tomgroenfeldt/2012/08/03/e-commerce-style-big-data-analytics-meet-brick-and-mortar-retailers/>.

sites such as Monster.com) utilize data from users to deliver relevant search results. By collecting and analyzing user search terms and clicks on search results (known as “click-and-query” data), online search providers are able to refine and improve their services. Generally, the search result that users have clicked on previously in response to the same or similar queries can be a useful “signal” of the relevance of a particular result. Thus, click-and-query data can be a useful input into providing high-quality search services. Search providers also frequently experiment with changes to result pages, including the user interface, and collect data on how users interact with new or changed elements in order to assess the value of the modifications to users.²⁰

21. User data also enhances the ability of search providers to suggest “related searches” or recommend particular products in which the user is likely to be interested.²¹ For example, shoppers on Amazon are shown recommended products based both on their own data and data collected from other users.²² Amazon’s “Frequently Bought Together” section within a product results page might, for example, suggest adding a ream of paper and printer ink if the user is searching for a printer. Similarly, online publishers like CNN may utilize user data from social networks to recommend other articles to its users.²³ For travel websites, collecting and displaying user reviews can be a valuable service for consumers.²⁴

²⁰ See, e.g., Barry Schwarz, “Testing, Testing, Testing: A Recap Of Google’s Latest Search Tests,” Search Engine Land, November 21, 2013, available at <http://searchengineland.com/testing-testing-testing-a-recap-of-googles-latest-search-tests-177928>.

²¹ See, e.g., Jeff Julian, “Benefits of Marketers Having Your Information,” Digital Marketing Blog, July 10, 2013, available at <http://blogs.adobe.com/digitalmarketing/personalization/benefits-of-marketers-having-your-information/>: “With consumer data, marketers can anticipate future actions. They can do this by combining specific information with generalized information. The specific information is that which is specifically associated with a single user, information such as a user’s clicks or actions on ads. General information is conglomerate data based on certain factors, including the average clicks or actions for a certain demographic on ads. If marketers already know that a consumer likes technology and books, then the marketers may be able to anticipate that the consumer would like to see an e-reader.”

²² Michael Olson, “Why Social Data Could Power the Future of eCommerce Personalization,” Janrain, November 30, 2011, available at <http://janrain.com/blog/why-social-data-could-power-future-ecommerce-personalization/>.

²³ See, e.g., “Help/Facebook Connect,” CNN, available at <http://edition.cnn.com/help/social/>.

²⁴ For instance, a recent survey found that 81 percent of travel searchers found user reviews “important.” (“Internet Travel Hotel Booking Statistics,” Statistic Brain, citing research by eSearch, eMarketer, and Alexa.com as of May 25, 2014, available at <http://www.statisticbrain.com/internet-travel-hotel-booking-statistics/>.)

22. User data also can help personalize the services of online providers.²⁵ One way providers can personalize their services is to utilize “social” data, such as the profiles entered on social networks like Facebook.²⁶ This type of user data allows online providers to identify products, content, or advertisements that a user is most likely to find useful.²⁷ Online providers also may utilize data regarding user location, which can help providers deliver products, services, or offers that are customized to a user’s physical location.²⁸ Studies have shown that consumers recognize the benefits of targeted, personalized marketing, and are willing to allow retailers to collect and use “their personal data in order to present personalized and targeted products, services, recommendations and offers.”²⁹

2. User data allows online providers to monetize effectively and thereby offer services at lower (often zero) prices to users

23. Online providers also utilize user data in order to monetize their services effectively. In online commerce, “monetization” refers to a provider’s ability to generate revenue from the content, services, or products offered to users, which are often provided for free. Many, if not most, online providers (as well as many traditional, offline firms) monetize their services through the showing of advertisements to users.

24. Advertisers want to reach potential customers as efficiently as possible. One mechanism for achieving this is through “targeted advertising,” whereby advertisements are placed so as to

²⁵ Personalization does not necessarily require a large scale of users. At its most basic level, personalization merely requires information regarding a specific customer.

²⁶ This data may include user-provided information on a customer’s interests, hobbies, and lifestyle, and may include similar information from other users in the customer’s “social circle.”

²⁷ See, e.g., Amanda Nelson, “How to Use Social Media Data for Customer Insight,” ExactTarget, December 26, 2013, available at <http://www.exacttarget.com/blog/social-media-data/>: “[a user’s] Facebook profile contains [the user’s] birth date, marital status, location, interests and more. [A user’s] LinkedIn profile contains [the user’s] work history, [a user’s] Paypal profile contains [the user’s] shipping address, and they all contain a verified email address. Using this type of information, marketing professionals can better segment their customers and prospects, and offer more relevant and personalized offers, promotions, and experiences. And this data is fairly easy to collect, as it can be accessed – with permission from the end user – when he/she uses an identity from one of these networks to register or login to a website using social login.”

²⁸ Mobile apps such as Coupons.com, Retailmenot, and FindandSave send “push” notifications to users to alert them of deals or specials at retail stores near the user’s physical location. (Greg Sterling, “Will New Foursquare App, Push Notifications, Boost Engagement?,” MarketingLand, December 6, 2013, available at <http://marketingland.com/will-new-design-push-notifications-boost-foursquare-engagement-67394>.)

²⁹ Grace Nasri, “Why Consumers Are Increasingly Willing to Trade Data for Personalization,” Digital Trends, December 10, 2012, available at <http://www.digitaltrends.com/social-media/why-consumers-are-increasingly-willing-to-trade-data-for-personalization/#ixzz2x28AHijj>.

be seen by consumers that are most likely to be interested in the products or services of the advertiser and/or most likely to respond to the advertisement by making a purchase, becoming aware of a product or brand, or obtaining information about a product. Advertisements can be targeted based on demographics, consumer interests, or behavioral traits (such as a user's web browsing behavior or product purchase history).³⁰

25. Both the monetization of services through the showing of advertisements to customers, and the targeting of advertisements, is economically-rational, profit-maximizing behavior. Targeted advertising is widespread in all industries, both online and offline, and by firms of all types and sizes. For instance, television networks and advertising agencies track the viewing activity and interests of consumers, using data from third-party market research companies such as Nielsen.³¹ This allows firms to place advertisements during television shows that are viewed by the subset of consumers most likely to respond to the advertisement. The ability to offer targeted ads is not limited to large providers—for instance, the Digital Advertising Alliance noted recently that small online providers derive 60 percent of their revenue from targeted ads.³²

26. Microsoft, Yahoo!, Facebook, Apple, Amazon, Google, and many other online providers collect and utilize user data to target ads to users.³³ Search ads, which are advertisements that appear on a search result page, are targeted to search queries inputted by users. Although, to a

³⁰ Targeted advertising that is based on consumer behavior is sometimes known as “behavioral targeting.” See, e.g., Howard Beales, “The Value of Behavioral Targeting,” 2010, p. 1, available at http://www.networkadvertising.org/pdfs/Beales_NAI_Study.pdf.

³¹ Although Nielsen has a long history of collecting user data on television viewing habits, new entrants like comScore and Rentrak also offer audience tracking data. (Amol Sharma & Christopher Stewart, “Nielsen Feels Digital Heat From Rivals,” *The Wall Street Journal*, February 12, 2014, available at <http://online.wsj.com/news/articles/SB10001424052702304703804579378973829456660>.)

³² Katy Bachman, “Advertisers Pay 3 Times More for Cookie-Based Ads,” *AdWeek*, February 10, 2014, available at <http://www.adweek.com/news/technology/study-interest-based-ads-are-workhorse-internet-155616>.

³³ Facebook: “We may also put together data about you to serve you ads or other content that might be more relevant to you.” (“Information we receive and how it is used,” Facebook, available at <https://www.facebook.com/about/privacy/your-info>.) Apple: “Apple and its partners use cookies and other technologies in mobile advertising services to control the number of times you see a given ad, deliver ads that relate to your interests, and measure the effectiveness of ad campaigns.” (“Apple Privacy Policy,” available at <https://www.apple.com/legal/privacy/en-ww/>.) Amazon: “Cookies are unique identifiers that we transfer to your device to enable our systems to recognize your device and to provide features such as ... personalized advertisements on other Web sites ...” (“Amazon.com Privacy Notice,” available at <http://www.amazon.com/gp/help/customer/display.html?nodeId=468496>.) Yahoo!: “Yahoo uses information for the following general purposes: to customize the advertising and content you see ...” (“Yahoo! Privacy Center,” available at <http://info.yahoo.com/privacy/us/yahoo/details.html>.) Bing Privacy Statement, available at <http://www.microsoft.com/privacystatement/en-us/bing/default.aspx>; Google Privacy Policy, available at <http://www.google.com/policies/privacy/>.

large extent, advertisers target their own ads to user queries by choosing keywords, bids, and other criteria (e.g., keyword match types, “partner” sites where ads will be shown), a search platform’s ad-targeting systems also are important. For example, Google determines where to show each advertisement on the search results page based on the Ad Rank, a measure which incorporates the advertiser’s bid and the advertisement’s “Quality Score,” which is based on Google’s prediction of the relevance and usefulness of the advertisement, keywords chosen by the advertiser, and the advertiser’s landing page.³⁴ Data collected from users, including click-and-query data, is valuable in determining the relevance and usefulness of particular advertisements in response to user search queries. Other types of online providers similarly target advertisements to user searches. For instance, Kayak’s proprietary advertising platform allows an airline to only show ads to users searching for routes where the airline offers service, or for a hotel to only show ads to users making travel plans during times the hotel has low occupancy.³⁵

27. User data also can help target other types of online ads, including display ads. For example, Facebook shows ads to users of its social network, which can be targeted based on various user characteristics, including location, demographics, interests, and user behavior.³⁶ As another example, ad targeting firms may track, through the use of cookies, a user that reads a news story about a new car model, and then can target display ads to that user (such as an advertisement about the new car model in which the user has expressed an interest).³⁷

³⁴ Google AdWords, “Check and understand Quality Score,” available at <https://support.google.com/adwords/answer/2454010?hl=en>. Advertiser quality also may be affected by other factors, such as whether the advertisement is accurate and truthful, promotes a legal product or service, and does not incorporate malware, spam or other unsafe practices. (See, e.g., AdWords Policy Center, available at <https://support.google.com/adwordspolicy/answer/1316548?hl=en>.)

³⁵ Kayak Software Corporation 2012 10-K, p. 3.

³⁶ See, e.g., “Top Targeting Options,” Facebook for Business, available at <https://www.facebook.com/business/products/ads/>. See also, Jason Ankeny, “How Small Companies Are Marketing Through Facebook,” Entrepreneur, May 24, 2011, available at <http://www.entrepreneur.com/article/219643>.

³⁷ See, e.g., Judith Aquino, “Ad Targeting Firm Semcasting Rolls Out Tool To Connect Online And Offline Data,” Ad Exchanger, October 8, 2013, available at <http://www.adexchanger.com/data-exchanges/ad-targeting-firm-semcasting-rolls-out-tool-to-connect-online-and-offline-data/>. See also, Laura Sydell, “Smart Cookies Put Targeted Online Ads On The Rise,” NPR, October 5, 2010, available at <http://www.npr.org/templates/story/story.php?storyId=130349989>. A recent economic study of targeted advertising found that “[o]nline advertising that uses cookie technology to increase relevance by leveraging consumers’ information generates significantly greater economic value than advertising without cookies.” (“Study: Online Ad Value Spikes When Data Is Used to Boost Relevance,” February 10, 2014, referencing J. Howard Beales & Jeffrey A. Eisenach, “An Empirical Analysis of the Value of Information Sharing in the Market for Online Content,”

28. The ability of online providers to monetize their services effectively through the use of targeted advertisements generates significant consumer benefits. In particular, the ability to monetize effectively creates incentives to attract users by offering high-quality services at low or even zero prices.³⁸ This is because the greater the advertising revenues that a provider can earn from each user, the greater the benefits of attracting and retaining users. Thus, the ability to earn greater advertising revenues enhances competition for users, creating incentives for providers to invest in improving the quality of services offered and to offer those services to users at low or zero prices.³⁹ The targeting of advertisements, including through the collection and utilization of user data, therefore generates huge consumer benefits.⁴⁰ Conversely, restricting the ability of online providers to collect and utilize data from users to target ads would inhibit competition for users and lead higher quality-adjusted prices for online services.

29. It has been claimed that the targeting of advertisements by online providers is more likely to harm consumers than ad targeting by traditional firms because online providers utilize user data to target advertisements more narrowly to individual users, rather than broad customer

[Navigant Economics, January 2014](http://www.aboutads.info/study-online-ad-value-spikes-when-data-used-boost-relevance), available at <http://www.aboutads.info/study-online-ad-value-spikes-when-data-used-boost-relevance>.)

³⁸ See, e.g., Adam Thierer, “Relax and Learn to Love Big Data,” U.S. News and World Report, September 13, 2013, available at <http://www.usnews.com/opinion/blogs/economic-intelligence/2013/09/16/big-data-collection-has-many-benefits-for-internet-users> (“[D]ata collection means all consumers enjoy a fuller range of goods and services, usually at a very low price.”).

³⁹ This interconnection between the different sides of a multi-sided platform—in this case, the advertising and the user sides—and the fact that improving monetization on one side tends to decrease prices and increase quality on the other, has been discussed extensively in the economics literature on “two-sided” markets. See, e.g., Benjamin Klein, Andres V. Lerner, Kevin M. Murphy & Lacey L. Plache, *Competition In Two-Sided Markets: The Antitrust Economics Of Payment Card Interchange Fees*, 73 ANTITRUST L.J. 571 (2006); Richard Schmalensee, *Payment Systems and Interchange Fees*, 50 J. INDUS. ECON. 103 (June 2002); Jean-Charles Rochet & Jean Tirole, *Cooperation Among Competitors: Some Economics of Payment Card Associations*, 33 RAND J. ECON. 549 (Winter 2002); Julian Wright, *The Determinants of Optimal Interchange Fees in Payment Systems*, 52 J. INDUS. ECON. 1 (Mar. 2004); Richard Schmalensee, *Interchange Fees: A Review of the Literature*, 1 PAYMENT CARDS ECONOMIC REV. 25 (Winter 2003); Sujit Chakravorti, *Theory of Credit Card Networks: A Survey of the Literature*, 2 REV. OF NETWORK ECON. 50 (June 2003); Jean-Charles Rochet, *The Theory of Interchange Fees: A Synthesis of Recent Contributions*, 2 REV. OF NETWORK ECON. 97 (June 2003).

⁴⁰ A study by McKinsey & Company, a consultancy, estimated that the consumer surplus from advertising-funded online services in the U.S. and Europe was €100 million (or roughly \$134 billion U.S. as of August 2014). This was “more than three times current revenue from ad-based services. In other words, the scale of online advertising revenue significantly underscores the massive value consumers derive from the online services they use.” (“Consumers driving the digital uptake: The economic value of online advertising-based services for consumers,” IAB Europe, September 2010, available at http://www.youronlinechoices.com/white_paper_consumers_driving_the_digital_uptake.pdf.)

groups.⁴¹ The more highly-targeted nature of online ads is claimed to be a more intrusive invasion of privacy, and more harmful to consumers, than offline ads. This claim is erroneous for a number of reasons. For starters, while traditional advertising historically was targeted at relatively large subsets of consumers, such targeting is becoming more granular and individualized.⁴² Moreover, there is no basis for the claim that the highly-targeted nature of online advertisements harms consumers. In fact, consumers seem to prefer advertisements that are targeted to their interests. In one recent poll, 40.5 percent of respondents indicated that they prefer targeted to non-targeted advertisements, while less than 5 percent of respondents had an unfavorable opinion of behaviorally-targeted advertisements.⁴³ Research also shows that *non-targeted* advertisements often are perceived as more intrusive than targeted advertisements by consumers.⁴⁴

30. Some commentators also have claimed that targeted advertising by online providers harms users because such advertising can compel consumers to purchase products or services they do not need.⁴⁵ Whatever one believes are the social merits of advertising, this is a criticism

⁴¹ For instance, Nathan Newman claims that, in contrast to traditional media markets, Google sells advertisers “access not to a particular media product” “but to each individual user based on their particular interests, demographic characteristics, location and the range of other information Google is able to identify about those advertising targets.” (Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, NYU Information Law Institute, last revised August 14, 2014, p. 9.)

⁴² See, e.g., Ryan Beene, “Data mining personalizes direct mail,” *Automotive News*, August 26, 2013, available at <http://www.autonews.com/article/20130826/RETAIL03/308269963/data-mining-personalizes-direct-mail>, describing direct mail targeting customers with new-vehicle lease and purchase offers tailored to specific customers, “right down to the desired monthly payment.” In the pay television market, “DirecTV combines data it collects from viewing habits from its customers’ digital video recorders with information from third-party market researchers in categories such as income, gender, age and buying habits. . . . ‘We can target based on demographics, household income, geo-targeting, home owners versus rental - a wide variety,’ said Paul Guyardo, chief revenue and marketing officer for DirecTV. This makes commercials more relevant to customers and ‘can move dollars back into national television because we can provide the same targeting as online ads,’ Guyardo said.” (Liana B. Baker & Lisa Richwine, “Cable Companies Mining Viewer Data For Targeted Ads,” *Huffington Post* (Reuters), June 27, 2013, available at http://www.huffingtonpost.com/2013/06/27/cable-companies-targeted-ads-data_n_3507487.html.)

⁴³ “Consumers Say They Prefer Targeted to Random Online Ads,” *Marketing Charts*, citing research by Zogby Analytics, April 19, 2013, available at <http://www.marketingcharts.com/wp/online/consumers-say-they-prefer-targeted-to-random-online-ads-28825/>.

⁴⁴ One study found that “almost 60% of consumers agree that online ads are annoying if they are not relevant to their interests.” (Karl Lendenmann, Ph.D., “Consumer Perspectives on Online Advertising – 2010,” PreferenceCentral Benchmark Research Study, p. 44.)

⁴⁵ Nathan Newman uses the example of subprime mortgages during the housing bubble. In particular, he states that “Google’s profiling of its users for advertisers allows the kind of predatory marketing we saw in the subprime housing bubble globally and in a range of other sectors.” (Nathan Newman, *The Costs of Lost Privacy: Consumer Harm and Rising Economic Inequality in the Age of Google*, 40(2) WILLIAM MITCHELL L. REV. 849, 857 (2014).)

applicable to all advertising, not just targeted online ads. Furthermore, it is widely recognized that advertising can have procompetitive effects, by increasing consumer access to information about firms' products, prices, and quality.⁴⁶ In any case, the welfare effects of advertising are not a competition policy, or an issue unique to user data collected by large online providers.⁴⁷

31. Another criticism of advertising-funded online services is that it makes it difficult for rivals to compete because it leads to low or zero prices to users. For instance, Nathan Newman claims that “by making these products free on the Internet, part of Google’s model is to largely destroy alternative revenue models and potential competitors...”⁴⁸ This critique turns the procompetitive effects of targeted advertising on its head. The fact that online providers, through the use of targeted advertising can provide customers high-quality online services for free to users may indeed make it more difficult for some rivals with particular business models to compete. But this is a procompetitive effect, not anticompetitive exclusion. Newman’s critique confuses harm to competitors with harm to competition. Mere harm to competitors—without harm to the competitive process itself—is not anticompetitive or detrimental to consumers.⁴⁹

⁴⁶ See, e.g., Kyle Bagwell, *Chapter 28: The Economic Analysis of Advertising*, in 3 HANDBOOK OF INDUSTRIAL ORGANIZATION 1703, 1706 (Mark Armstrong & Robert Porter eds., 2007): “When a firm advertises, consumers receive at low cost additional direct (prices, location) and/or indirect (the firm is willing to spend on advertising) information. The firm’s demand curve becomes more elastic, and advertising thus promotes competition among established firms. As well, advertising can facilitate entry, as it provides a means through which a new entrant can publicize its existence, prices and products. The suggestion here, then, is that advertising can have important pro-competitive effects.” The value of advertising also has been recognized by many courts. (See, e.g., *Virginia State Bd. of Pharmacy v. Virginia Citizens Consumer Council*, 425 U.S. 748, 765 (1976).)

⁴⁷ Nathan Newman also argues that online providers’ collection and utilization of user data for targeted advertising leads to an “information asymmetry,” whereby companies have better knowledge of their potential consumers than consumers have of potential provider options and that, as a result, “market equilibriums are no longer necessarily stable and consumers (and regulators) cannot depend on the market to deliver optimal consumer welfare.” (Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, last revised August 14, 2014, NYU Information Law Institute, pp. 4-5, forthcoming 40(3) YALE J. OF REGULATION (2014).) However, the existence of perfectly-informed consumers, although a theoretical assumption of economic models of perfect competition, is not required for markets to be highly competitively in the real world. Neither does effective competition require that consumers have equivalent information and knowledge as the firms that supply them. There is incomplete information, and information asymmetries, in every real-world industry, but this does not imply that these industries are not competitive.

⁴⁸ Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, last revised August 14, 2014, NYU Information Law Institute, p. 18, forthcoming 40(3) YALE J. REG. (2014).

⁴⁹ For instance, lower prices make it more difficult for rivals to compete, but lower prices are the essence of competition.

32. Zero or negative pricing on one side of the market does not involve predatory pricing.⁵⁰ Because such zero pricing leads to monetary benefits on the other side of the platform—*i.e.*, advertisement revenues—a strategy of monetizing through targeted advertisements and offering services for free to users is economically rational even if “recoupment” from users were not feasible, which is a necessary element of anticompetitive predatory pricing.⁵¹ As noted, the monetization of services by means of advertising is widespread both for online and offline providers and many advertising-funded businesses (including newspapers, television networks, and radio networks) offer services for free to consumers. The fact that many, if not most, online providers (as well as many traditional media firms) have similar strategies of offering services for free and monetizing through advertisements also indicates that this strategy is a normal part of the competitive process and not an anticompetitive pricing strategy by dominant online providers.⁵²

33. In sum, the collection and utilization of user data to improve services and monetize effectively leads to the provision of better services at lower or zero prices to consumers. The collection of user data, rather than being the consequence or cause of the absence of competition, is a competitive necessity for most online providers. While the collection of user data is a crucial aspect of competition for most online providers, this does not mean that online providers are unrestrained in doing so. Competition compels online providers to achieve an efficient balance between the consumer benefits from collecting user data with users’ demand for privacy. Although this balance will vary across different types of providers, most reputable online providers will bear a significant cost in terms of reduced demand if they overstep user privacy

⁵⁰ See, *e.g.*, Benjamin Klein, Andres V. Lerner, Kevin M. Murphy & Lacey L. Plache, *Competition In Two-Sided Markets: The Antitrust Economics Of Payment Card Interchange Fees*, 73 ANTITRUST L.J. 571 (2006); David S. Evans, *The Antitrust Economics of Multi-Sided Platform Markets*, 20 YALE J. REG. 325 (2003).

⁵¹ *Brooke Group Ltd. v. Brown & Williamson Tobacco Corp.*, 509 U.S. 209 (1993).

⁵² Massimo Motta & Helder Vasconcelos, “Exclusionary Pricing in a Two-Sided Market,” Centre for Economic Policy Research, Discussion Paper No. 9164 (2012) provides a theoretical model of predation in a two-sided market context which involves a platform owner that engages in predation on one side of a two-sided platform (*e.g.*, users) in order to monopolize, and charge supracompetitive prices, on the other side of the platform (*e.g.*, advertising). The authors explain that “sacrificing profits on one side allows the dominant incumbent to enjoy monopoly profits on the other side, thus providing a rationale for predation.” However, the fact that small providers and new entrants implement such a pricing structure indicates that zero pricing to users is profitable absent any attempt to monopolize the advertiser side of online markets. In fact, Motta and Vasconcelos explain that “in most cases,” below cost pricing on one side of a two-sided market does not involve predation, or a threat to competition, and may be necessary to “get both sides on board.”

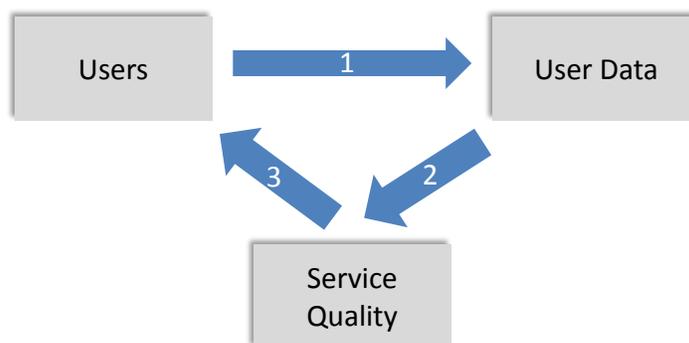
norms. This is especially true for ad-supported online businesses, which are dependent on attracting users in order to monetize through the sale of advertisements.

III. The Collection of User Data Does Not Lead to the Entrenchment of Dominant Online Platforms

34. Proponents of greater antitrust scrutiny of large online firms seem to recognize that the collection of user data leads to the provision of better services and lower prices, but claim that because of these competitive benefits of user data, having significant amounts of data leads to insurmountable advantages to large online providers, and thus to the eventual entrenchment of dominant providers.

35. There are two claimed theories regarding how the collection of user data leads to the entrenchment of dominant online platforms. First, it is argued that more users allow a platform to collect more user data (step 1 in Figure 1 below) which, in turn, allows the provider to offer superior services (step 2), and thereby attract even more users (step 3). According to this theory, small providers and new entrants cannot compete effectively for users vis-à-vis larger incumbents because the lack of comparable amounts of user data prevents them from offering services of equivalent quality to users.⁵³ This alleged feedback-loop is depicted in Figure 1 below:

Figure 1: Claimed User Scale-Service Quality Feedback Loop



⁵³ See, e.g., Frank A. Pasquale, *Privacy, Antitrust, and Power*, 20 GEO. MASON L. REV. 1009, 1015 (2013), claiming that because of this “self-reinforcing data advantage of dominant firms, there is unlikely to be much competition in search and social networking.”

Second, it is claimed that the collection of data from a large base of users allows a provider to better monetize its platform, which, in turn, allows the provider to make investments necessary to attract even more users. It is argued that, as a result of these powerful “feedback loops,” online providers need a lot of users from whom to collect data, and a lot of data to effectively compete for users and advertisers. These feedback loops are assumed to lead to large economies of scale, and to “tipping” of online markets towards dominant players.⁵⁴ As I discuss below, these assumptions regarding user data feedback loops are unsupported by real-world evidence.

36. Before addressing the competitive effects of the claimed feedback loops, it is important to note that the mere existence of economies of scale does not, by itself, establish that large providers have monopoly power, that large providers have acted anticompetitively, or that consumers or competition have been harmed. Neither does the fact that there are economies of scale mean that large online providers should be subject to greater antitrust scrutiny. In fact, the existence of economies of scale means that there are benefits of scale, and that consumers may benefit from the existence of large providers through higher quality and/or lower prices. Regulating large firms simply because there are economies of scale would serve as a tax on competitive success, distorting competition and harming consumers.

A. Foreclosure of rivals through the collection of user data is highly unlikely

37. It is claimed that smaller firms and new entrants cannot compete effectively against larger rivals because they do not have access to large amounts of user data. These claims are based on the assumptions that: (1) user data is an essential input and large amounts of user data is necessary to compete effectively; and (2) large incumbent online providers somehow foreclose smaller rivals from access to this essential input through their “control” of all or most data available from users. In Sections B and C below, I explain that the first claim—that online providers need large troves of user data to compete effectively—is overstated in practice. In this section, I explain that assumption (2) also is incorrect. Large, incumbent online providers do not inhibit smaller rivals from collecting and/or purchasing user data, and no one firm “controls” all, most, or even a significant share of user data. Online providers do not have actual or *de facto* exclusivity over user data, and user data is a non-rival good, which means that many websites

⁵⁴ In contrast to the usual economies of scale in which *costs decrease* at higher quantity, these arguments assume that *quality increases* with higher scale.

can collect data from the same users, and often even for the same type of user activity. As a result, many providers, including providers that compete to offer similar services to users, have access to large amounts of user data.

1. *User data is non-rivalrous and incumbent online providers do not have (explicit or de facto) exclusivity over user data*

38. Economic theories of “vertical foreclosure”—*i.e.*, foreclosure through control of an input—are based on a dominant firm depriving rivals of access to an essential input (such as retailing or distribution) either (1) through the purchase of exclusionary rights (such as exclusive contracts) from owners of an essential input⁵⁵ or (2) by overpaying for such an input.⁵⁶ In theory, the lack of access to an essential factor of production can keep rivals below minimum efficient or viable scale, which can drive rivals out of business and/or can relax the competitive constraint that rivals can exert on incumbents.

39. In contrast to these theories of foreclosure from an essential input, there is no exclusivity in the collection of user data by online providers. There are no exclusive contracts with users, and no pricing structure (such as loyalty discounts) that locks-in users to a particular platform. Large online providers do not have exclusive access to any user. User data also is “non-rivalrous,” meaning that collection and use by one provider does not detract from collection and use by others.⁵⁷ Thus, collecting data from some users does not prevent or inhibit rivals from collecting data from those same users.

⁵⁵ See, *e.g.*, Eric B. Rasmusen, J. Mark Ramseyer & John S. Wiley, Jr., *Naked Exclusion*, 81(5) AMER. ECON. REV. 1137 (1991); Thomas G. Krattenmaker & Steven C. Salop, *Anticompetitive Exclusion: Raising Rivals’ Costs to Achieve Power Over Price*, 96(2) YALE L. J. 209 (1986); Michael D. Whinston, *Tying, Foreclosure, and Exclusion*, 80(4) AMER. ECON. REV. 837 (1990). Other theories of vertical foreclosure pertain to the ability of a vertically integrated firm to deny access to an essential input to rivals. (See, *e.g.*, Michael H. Riordan & Steven C. Salop, *Evaluating Vertical Mergers: A Post-Chicago Approach*, 63(2) ANTITRUST L. J. 513 (1995); Jeffrey Church, *Vertical Mergers*, in 2 ISSUES IN COMPETITION LAW AND POLICY 1455 (ABA Section of Antitrust Law, 2008); Janusz A. Ordover, Steven C. Salop & Garth Saloner, *Equilibrium Vertical Foreclosure*, 80 (1) AMER. ECON. REV. 127 (1990).)

⁵⁶ See, *e.g.*, Steven C. Salop, *Anticompetitive Overbuying by Power Buyers*, 72(2) ANTITRUST L. J. 669 (2005); John B. Kirkwood, *Buyer Power and Exclusionary Conduct: Should Brooke Group Set the Standards for Buyer-Induced Price Discrimination and Predatory Bidding?*, 72(2) ANTITRUST L.J. 625 (2005); Richard O. Zerby, Jr., *Monopsony and the Ross-Simmons Case: A Comment on Salop and Kirkwood*, 72(2) ANTITRUST L. J. 717 (2005).

⁵⁷ A rival good is a good whose consumption by one consumer prevents simultaneous consumption by other consumers.

40. In practice, the lack of exclusivity over users is reinforced by the fact that users tend to utilize, and share their information with, a variety of different online platforms. The practice of participating in two or more platforms simultaneously is referred to as “multi-homing.”⁵⁸ Platform participants can benefit from multi-homing when different networks offer different features, functions, or quality levels. And, in online markets, costs to users of switching platforms or multi-homing are very low.⁵⁹ As a result, there is extensive user multi-homing whether one looks at websites that provide similar services (*e.g.*, general search providers such as Bing, Yahoo!, Google, and Ask!) or differentiated websites that nevertheless may compete for users with regard to a particular activity (*e.g.*, Amazon and Google).

41. With regard to providers of general search, data from Nielsen indicate that 59 percent of Google users also visited Bing, Yahoo!, or Ask! during the course of one month.⁶⁰ A survey by Forrester Research found that 55 percent of users use more than one search engine on a weekly basis.⁶¹ A study by Microsoft researchers based on browser toolbar data found that 72.6 percent of users in their sample used more than one search engine.⁶² The study also found that 50 percent of users in their sample had switched search engines within the same search session at least once.⁶³

42. There is also evidence of multi-homing across providers that offer differentiated search services, such as specialized search providers. For travel-related search, surveys indicate that consumers utilize multiple sites to research and book travel, including general search engines and

⁵⁸ For instance, in the context of payment cards, merchants generally multi-home by accepting various general purpose credit and charge cards, such as cards issued by Visa, MasterCard, American Express, and Discover. Similarly, most consumers multi-home by carrying the cards of multiple payment networks.

⁵⁹ See, *e.g.*, Aaron S. Edlin & Robert G. Harris, *The Role of Switching Costs in Antitrust Analysis: A Comparison of Microsoft and Google*, 15 YALE J. L. TECH. 169 (2013).

⁶⁰ Nielsen NetView data for December 2011. Nielsen has a panel of representative Internet users for which it tracks all online activity, including search engine usage.

⁶¹ North American Technographics Retail Online Survey, Q3 2008, cited in: Shar VanBoskirk, “Search Loyalty is Still Hard to Find, Advertising Options Exist Beyond Just Google,” Forrester Research, February 3, 2009.

⁶² Ryan W. White & Susan Dumais, “Characterizing and Predicting Search Engine Switching Behavior,” Microsoft Research, November 2009, available at <http://research.microsoft.com/en-us/um/people/sdumais/cikm2009-switching-fp1012-white.pdf>. The study analyzed six months of interaction logs from September 2008 - February 2009. Of the 14.2 million users in the log sample, 10.3 million used more than one engine in the six-month period.

⁶³ Of the 14.2 million users in the log sample, 7.1 million switched search engines within a search session at least one time.

vertical search sites specializing in travel.⁶⁴ Similarly, in searching for products, a recent study found that most consumers use multiple sites to conduct research on brands and products, including a search engine, a product review site, and the manufacturer’s website.⁶⁵ The significant user multi-homing for online activities reflects the fact that online services are highly differentiated and, thus, there is often value to users of utilizing multiple platforms that may provide different information or services related to a particular user task (an issue that I discuss in Section IV.B). Because of significant multi-homing by users, rival online providers have access to data from the same individual users, and access to user data is unlikely to create a material barrier to entry and competition.

43. As noted, other theories of depriving rivals of access to an essential input are related to a firm “overpaying” for such an input. In this case, such a theory would mean that large online providers “overcompensate” users for the value of the data that they provide—*e.g.*, offer too many valuable services for free—such that the provision of such services would not be profitable absent an attempt to exclude rivals. However, the provision of valuable free services and collection of user data by large online providers is beneficial not because it deprives rivals of such data, but because of the procompetitive reason that it improves the ability of an online provider to offer high-quality services and target advertisements effectively.⁶⁶

2. *No one firm controls all, most, or even a significant share of user data*

44. Claims that the collection of user data has led to the entrenchment of dominant online platforms also is belied by the fact that no one firm controls all, most, or even a significant share of user data. Many online providers have access to large amounts of user data. For instance, in the provision of general search, firms such as Bing obtain a substantial amount of user data from a variety of sources. First, Bing has significant scale of users—its query volume is almost half

⁶⁴ PhoCusWright conducted a survey in 2010 asking users “When planning leisure travel, how many Web sites do you typically visit when [shopping]?” The results show that 59 percent of respondents use 3 or more websites to shop for travel and the remaining 41 percent use one or two sites. (Carroll Rheem, *Consumer Travel Report Second Edition*, PhoCusWright, May 2010, at 29, Figures 29, 30.)

⁶⁵ Colby Vogt & Ken Alldredge, “Understanding the role of the Internet in the lives of consumers – 2012 Digital Influence Index Annual Global Study,” Fleishman Hillard/Harris Interactive, 2012, p. 11, available at http://www.harrisinteractive.com/vault/HI_UK_Corp_Insights-Fleishman-Hillard-DDI-2012.pdf.

⁶⁶ Notably, a theory that online providers “overpay” users for the collection of their data is inconsistent with assertions that dominant online platforms “undercompensate” users (see discussion, Section IV.A).

that of Google, and continues to grow.⁶⁷ In a recent article, Bing’s head of Search Advertising described how Bing can “draw upon our enormous collection of click-and-query data” to enable advertisers to target advertisements effectively.⁶⁸ Bing also obtains user data from many sources other than its search engine (Bing.com), including toolbar and browser data. Bing logs all user pageviews through its Bing Toolbar and its Internet Explorer browser (unless a user opts-out), and has large amount of browser data as a result of Microsoft’s substantial share of browsers.⁶⁹ In fact, through the Bing toolbar and Internet Explorer browser, Bing has access to click-and-query data for searches conducted on the Google platform, and Bing has used this information in its search algorithm.⁷⁰ In addition, Bing has access to user data from online social network providers like Facebook and Twitter.⁷¹

45. There are many types of user data that are valuable for providing online services, and the value of having access to any particular type of data varies depending on the services provided and the competitive strategy of the online provider. It is not just the sheer scale of user data that is important to online providers, but how useful the data is in improving the services offered by

⁶⁷ In March 2014, Bing received roughly 5.6 billion queries in the U.S. alone, which is about 43 percent of the U.S. query volume of Google. (comScore press release, “comScore Releases March 2014 U.S. Search Engine Rankings,” April 15, 2014, available at http://www.comscore.com/Insights/Press_Releases/2014/4/comScore_Releases_March_2014_U.S._Search_Engine_Rankings.)

⁶⁸ John Cosley, “Put Big Data To Work To Build Better Search Ads,” Search Engine Land, May 28, 2014, available at <http://searchengineland.com/putting-big-data-work-building-better-search-ads-191432>.

⁶⁹ Data on user page views may be sent to Bing from Internet Explorer, which can send data to Microsoft via its Suggested Sites feature, and from the Bing Toolbar, which can send data via Microsoft’s Customer Experience Improvement Program. (See, e.g., “Bing: Another Shot at Search,” Directions on Microsoft, June 14, 2009, available at <https://web.archive.org/web/20130917192457/http://www.directionsonmicrosoft.com/samples/49-samples/1943-bing-another-shot-at-search.html>: Microsoft “has used data collected from several million users who have installed the Windows Live or MSN Toolbars and opted in to allow Microsoft to track their Web activity in order to improve Microsoft products.”)

⁷⁰ Matt Rosoff, “Yes, Bing Has Been Copying Google Search Results FOR YEARS,” Business Insider, February 1, 2011, available at http://articles.businessinsider.com/2011-02-01/tech/29975847_1_bing-director-stefan-weitz-satya-nadella-msn-toolbar.

⁷¹ Bing announced an arrangement with Facebook in October 2009 that provides Bing with a real-time feed of Facebook updates that users chose to make public. The arrangement enhances Bing search results by introducing Facebook powered “Liked Results” as well as displaying Facebook Profile Results in response to searches for individuals. Bing also announced a deal with Twitter in October 2009 that gives Bing access to Twitter data for Bing to use in providing search results. (Kara Swisher, “Exclusive: Guess Who Else Is Coming to Dinner? Twitter-Microsoft Bing Deal Confirmed, But So Is Facebook-Bing,” AllThingsD, October 21, 2009, available at <http://allthingsd.com/20091021/exclusive-guess-who-else-is-coming-to-dinner-twitter-microsoft-bing-deal-confirmed-but-so-is-facebook-bing/>.) Bing announced the continuation of its deal with Twitter in November 2013. (Matt McGee, “Bing, Twitter Renew Deal To Include Tweets In Search Results,” Search Engine Land, November 1, 2013, available at <http://searchengineland.com/bing-twitter-renew-deal-to-include-tweets-in-search-results-175791>.)

the provider. Many types of specialized data may be more valuable, for certain purposes, than having a lot of general data. For instance, data on a specific type of user activity (e.g., user purchases) may be more valuable in providing a particular service (e.g., comparison shopping) than having lots of data across a wide range of activities, such as data on general searches conducted by users. Specialized sites collect user data that is valuable in supporting the products or services they offer:

- Amazon collects and analyzes many types of user data, including “login; e-mail address; password ... purchase history ... products [users] viewed or searched for; and the phone number [users] used to call our 800 number.”⁷² Amazon uses such data to recommend products based on a user’s personal data, inform users of similar products that other customers have purchased, and provide product reviews from other customers.⁷³ Amazon also collects pertinent user data like credit cards to enable easier customer checkout. Other shopping sites also collect similar types of information.
- Review-driven sites, such as travel planning site TripAdvisor, focus on amassing user reviews about specific travel destinations.⁷⁴ Similarly, Yelp, an “online urban guide,” collects and provides user reviews and business ratings.
- Social media sites such as Facebook collect demographic and behavioral data from their users through user profiles and user interactions with the website, including information

⁷² Additionally, for some user visits Amazon “may use software tools such as JavaScript to measure and collect session information, including ... length of visits to certain pages, page interaction information (such as scrolling, clicks, and mouse-overs), and methods used to browse away from the page.” (“Amazon.com Privacy Notice,” available at <http://www.amazon.com/gp/help/customer/display.html?nodeId=468496>.)

⁷³ An article in *Fortune* described how Amazon’s “recommendation system is based on a number of simple elements: what a user has bought in the past, which items they have in their virtual shopping cart, items they’ve rated and liked, and what other customers have viewed and purchased.” (JP Mangalindan, “Amazon’s recommendation secret,” *Fortune*, July 30, 2012, available at <http://tech.fortune.cnn.com/2012/07/30/amazon-5/>.)

⁷⁴ TripAdvisor offers incentives to users to submit reviews. For example, TripAdvisor partners with AmEx to provide special offers to AmEx cardholders who write reviews on TripAdvisor. (“American Express Card Members Travel Smarter with TripAdvisor,” available at https://sync.americanexpress.com/tripadvisor/?extlink=twitter_100813_001; American Express/TripAdvisor “Frequently Asked Questions: Our Offers in this Program,” available at <https://sync.americanexpress.com/Tripadvisor/FAQ#faq-offers>.) Similarly, Amazon invites “trusted” reviewers (based on their reviewer rank) to post reviews about new and pre-release items, as part of its Amazon Vine program. In return, Amazon provides its Vine members with free products offered by various Amazon vendors. (Amazon, “What is Amazon Vine?,” available at <https://www.amazon.com/gp/vine/help>.)

on a user's personal background (such as where a user attended school) and a user's personal interests ("likes").⁷⁵

- Netflix tracks user plays per day, user interaction (*i.e.*, rewind, fast forward and pause behavior), streaming, user ratings, location data, device information, and viewing time (*i.e.*, time of day and week).⁷⁶

46. Online providers also often forge partnerships in order to offer valuable content based on user data collected by other firms. For example, Yahoo! has partnered with Yelp to "incorporate Yelp's listings and reviews of local businesses into results on Yahoo's search engine..."⁷⁷ Apple has also partnered with Yelp, which allows Apple to offer high-quality local content such as business reviews to users of Apple mobile devices.⁷⁸ And, Apple's iOS7 mobile operating system features enhanced Twitter integration through Siri, the iPhone's personal assistant.⁷⁹

47. The fact that many competitors collect and/or purchase large amounts of data from various sources has been widely reported in the press. A *Forbes* article, for instance, explains that:

Meanwhile unanticipated competitors like Facebook, Amazon, Twitter and others continue to knock at Google's metaphorical door, all of them entering into competition with Google using data sourced from creative sources, and all of them potentially besting Google in the process. Consider, for example, Amazon's recent move into the targeted advertising market, competing with Google to place ads on websites across the Internet, but with the considerable advantage of being

⁷⁵ Hayley Tsukayama, "Facebook updates data use policy," *The Washington Post*, August 29, 2013, available at http://www.washingtonpost.com/business/technology/facebook-updates-data-use-policy/2013/08/29/3f0faa08-10cd-11e3-b4cb-fd7ce041d814_story.html.

⁷⁶ Netflix also obtains metadata from third parties such as Nielsen and social media data from Facebook and Twitter. (Derrick Harris, "Netflix analyzes a lot of data about your viewing habits," *GigaOM*, June 14, 2012, available at <http://gigaom.com/2012/06/14/netflix-analyzes-a-lot-of-data-about-your-viewing-habits/>.)

⁷⁷ Douglas MacMillan and Daisuke Wakabayashi, "Yahoo to Partner With Yelp on Local Search," *The Wall Street Journal*, February 10, 2014, available at http://online.wsj.com/news/article_email/SB10001424052702304680904579371263386333816-1MyQjAxMTA0MDAwODEwNDgyWj.

⁷⁸ Greg Sterling, "Yelp Elevated By Apple Relationship, Second Only To Google In Local Importance Now," *Search Engine Land*, June 25, 2012, available at <http://searchengineland.com/yelp-elevated-by-apple-relationship-second-only-to-google-in-local-importance-now-125824>.

⁷⁹ Danny Sullivan, "With iOS 7, Siri Drops Google For Bing, Also Gains Twitter Search," *Search Engine Land*, September 18, 2013, available at <http://searchengineland.com/with-ios-7-siri-drops-google-for-bing-172110>.

able to target ads based on searches, or purchases, a user has made on Amazon—the world’s largest product search engine.⁸⁰

Similarly, the U.S. Federal Trade Commission, in its statement closing its investigation of Google’s acquisition of DoubleClick, stated that:

The evidence indicates that neither the data available to Google...constitutes an essential input to a successful online advertising product. A number of Google’s competitors have at their disposal valuable stores of data not available to Google. For instance, Google’s most significant competitors in the ad intermediation market, Microsoft, Yahoo!, and Time Warner have access to their own unique data stores. These firms own popular search engines, and will have access to consumer information from their internal ad servers, ad intermediation services, other web properties, and software.... All of these firms are vertically integrated, and all appear to be well-positioned to compete vigorously against Google in this new marketplace.⁸¹

48. Lastly, it is worth noting that because the value of user data varies greatly, it would be difficult, if not infeasible, to estimate the share of user data collected by particular online providers for purposes of assessing the extent of “foreclosure.” As noted, there are many different kinds of user data, collected from a myriad of sources, and utilized in the provision of many different types of services. Some types of user data may be useful for some purposes, but not for others. Thus, any estimates of foreclosure from user data cannot be based on the volume of user data, or on the number of users contributing that data.

B. Competitive success of online platforms is driven by much more than the amount of user data collected

49. Claims regarding the entrenchment of online platforms—*i.e.*, that platforms with more users can provide superior services and more effectively monetize those services, and therefore

⁸⁰ Geoffrey Manne, “FTC Ends Google Antitrust Investigation. Critics And Competitors: Move On,” *Forbes*, January 3, 2013, available at <http://www.forbes.com/sites/beltway/2013/01/03/ftcs-google-antitrust-investigation-was-silly-critics-and-competitors-move-on/>.

⁸¹ Statement of Federal Trade Commission Concerning Google/DoubleClick, FTC File No. 071-0170, December 20, 2007, pp. 12-13, available at http://www.ftc.gov/system/files/documents/public_statements/418081/071220googledc-commstmt.pdf.

are protected from competition from smaller online providers—assume that competition between online platforms is largely unidimensional. In particular, the implicit assumption appears to be that the volume of user data is largely deterministic of the quality of services offered and the ability to monetize by targeting ads and, therefore, the only or principal way to improve quality is to increase the base of users. And, in order to expand the user base, online platforms require large volumes of user data to provide high quality services and monetize effectively. This description of the nature of competition between online providers, however, is far removed from reality—the firm with the most data does not necessarily win, and often does not win.⁸²

50. While data collected from users can be important to online providers in improving the services offered and their ability to monetize, user data is only one of many inputs into providing online services. The quality of services offered by online providers, and the ability to monetize effectively, is driven by much more than user data. There are many other sources of data, inputs into providing high quality services, dimensions of quality, and means of attracting users (such as distribution arrangements). Online providers can make investments in quality and distribution that are independent of its scale of users. And, through these investments, a provider can attain scale. Thus, it is incorrect to assert that an online platform lacking scale today can never attain scale. The fact that online providers can gain user scale in ways that do not involve user data weakens the claimed user data-service quality feedback-loop.

51. Other sources of data: There are many types and sources of data that can be used as inputs to the provision of online services. Take, for example, targeted search providers that offer search services on specific topics such as shopping, travel, and local interests. These providers have many sources of data that they can use to improve their services, including data from third-party data collection firms. Many of these online providers offer aggregation and comparison services (*e.g.*, for financial products, real estate, or consumer products), for which the primary source of the data used are “feeds” from firms offering these products and services (*e.g.*, banks, realtors, retailers). For instance:

⁸² In fact, causality may flow in the opposite direction—successful platforms have lots of users and therefore have access to lots of data, but the opposite is not necessarily true. Moreover, as I discuss in Section IV.B, online platforms are highly differentiated, and this differentiation reduces the likelihood that the market will “tip” to the firm with the most data.

- Comparison shopping sites such as Nextag offer products from many merchants, receiving data from each merchant through a data feed.⁸³
- Amazon gathers “detail page content” from vendors that wish to sell through Amazon, including a description of the product and features, and images of the product.⁸⁴
- Kayak, a travel metasearch site, “has multiple data sources, including ITA and Amadeus (third-party ‘faring engines’), and direct queries of dozens of online travel agencies, airlines, and discount consolidators.”⁸⁵ Kayak recently noted that its “commercial relationships include agreements with over 300 travel suppliers, OTAs and technology providers. These relationships provide [Kayak] with access to travel information, booking, fulfillment and customer service solutions.”⁸⁶
- Zillow gets data on new listings either directly from real estate agents, or from other online provider sites that syndicate real estate listings. Zillow’s historical real estate data is purchased from third-party data collection companies that assemble publicly-available county records data.⁸⁷
- Yelp, a local search provider, recently entered into a strategic partnership with YP (Yellow Pages) which gives Yelp access to YP’s business owner profiles.⁸⁸
- News sites may display traffic information and stock market data that are obtained from third-party suppliers.⁸⁹

⁸³ See, e.g., “Comparison-Shopping Engines: The Do’s & Don’ts of Three Popular CSEs, Part III,” Hanapin Marketing, June 24, 2013, available at <http://www.ppchero.com/comparison-shopping-engines-the-dos-donts-of-three-popular-cses-part-iii/>.

⁸⁴ “Creating Great Detail Page Content,” Amazon Help & Customer Service, available at <http://www.amazon.com/gp/help/customer/display.html?nodeId=12177401>.

⁸⁵ Lou Carlozo, “How Travel Website Kayak Sees the Future (Literally) with Price Forecasting,” Deal News, February 4, 2013, available at <http://dealnews.com/features/How-Travel-Website-Kayak-Sees-the-Future-Literally-with-Price-Forecasting/664706.html>.

⁸⁶ Kayak Software Corporation 2012 10-K, p. 6.

⁸⁷ “Where does Zillow get its data?” Zillow Questions, October 3, 2011, available at <http://www.zillow.com/advice-thread/Where-does-Zillow-get-its-data/418032/>.

⁸⁸ Greg Sterling, “Yelp and YP Enter Into “Strategic” Content, Distribution Partnership,” Search Engine Land, March 20, 2014, available at <http://searchengineland.com/yelp-yp-enter-content-distribution-partnership-187184>.

⁸⁹ See, e.g., Ben Kuo, “Interview with Jonathan Berke, Sigalert.com,” socialTECH.com, October 3, 2005, available at http://www.socialtech.com/interview_with_jonathan_berke_sigalert_com/s-0005615.html: “[Sigalert.com, a freeway traffic website] provide[s] web pages to other web sites—for example, the LA Times, NBC in LA, KABC

52. General search engines also utilize data from sources other than users. For example, Google uses factors such as its proprietary Page Rank algorithm and signals regarding the quality of a website that do not depend on user behavior. Search engines also receive many misspelled queries from users, and using various types and sources of data to “revise” these queries and return the desired result is an important aspect of search quality. While user data plays a role in spelling revisions, search engines also analyze “crawled” data from Internet websites to gauge common spellings and misspellings of words.⁹⁰ Search engines also purchase data from third parties that are used to answer particular user queries, including for sports scores, stock performance, weather forecasts, and currency exchange rates.⁹¹

53. Inputs other than data: There are also many inputs other than data in providing high-quality online services. For example, shopping and review firms such as CNET utilize professionally written reviews to aid users searching for the best products.⁹² Yelp hires temporary local employees, called “scouts”, to provide additional site content, such as reviews, photos, and hours of operation.⁹³ Content sites like the Huffington Post hire writers to generate articles and opinion pieces.⁹⁴

54. In online search as well, there are many different inputs to providing high quality search results, including engineering resources, innovation, and quality testing. A key determinant of search quality is the amount and caliber of engineering resources devoted to improving a search engine’s algorithms. Another important input for search providers is the provider’s web

in LA, KFWB, KNX, and lots and lots of media companies. [Signal.com] provide[s] traffic pages for them as well.” Another example is stock market data on BBC News, which is provided by DigitalLook.com. (See, e.g., http://www.bbc.com/news/business/market_data/overview/.)

⁹⁰ Dr. Jim Kleban, Program Manager - Bing R&D, “Building a State-of-the-Art Speller,” Bing Blog, January 3, 2013, available at <http://blogs.bing.com/search/2013/01/03/bing-search-quality-insights-building-a-state-of-the-art-speller/>.

⁹¹ Google sports scores are provided by STATS LLC (<http://www.google.com/intl/en/help/features.html>); Google stock performance data are provided by SIX Financial Information (exchange data) and Morningstar (mutual fund data) (<http://www.google.com/intl/en/googlefinance/disclaimer/?ei=Xoo8U6DdFYerqgHhRA>); Weather forecasts are provided by Weather Underground, Inc. (https://www.google.com/intl/en/help/features_list.html#weather). (<http://www.google.com/intl/en/googlefinance/disclaimer/?ei=Xoo8U6DdFYerqgHhRA>).

⁹² See, e.g., “CNET Reviews,” available at <http://www.cnet.com/about/cnet-reviews/>.

⁹³ Yelp Inc. 2012 10-K, p. 4.

⁹⁴ See, e.g., Jason Linkins, “How The Huffington Post Works (In Case You Were Wondering),” The Huffington Post, February 10, 2011, available at http://www.huffingtonpost.com/2011/02/10/huffington-post-bloggers_n_821446.html.

crawling and indexing technology.⁹⁵ The ability to quickly crawl and index new content, which relies on engineering ability, not user data, is vital in identifying results that are relevant to “fresh” queries—*i.e.*, queries regarding recent events and information.⁹⁶ Google identifies fresh queries primarily based on rapid increases in *content* on a particular topic, which can be observed from documents recently crawled, and large increases in relevant documents recently indexed.⁹⁷ For instance, Google observes whether there is a significant increase in news articles on a particular topic.⁹⁸

55. There also are inputs to service quality other than engineering resources. For instance, search engines use human raters to test and improve their algorithms. Google employs a large number of human search quality “Raters” to evaluate the quality and relevance of its search results.⁹⁹ Google also expends substantial resources to fight “spam” in its search results, including algorithmic screening and manual review.¹⁰⁰

⁹⁵ It has been reported that Google has developed superior web crawling and indexing capabilities compared to Bing and the size of Google’s index is larger than that of Bing. (See, *e.g.*, Christy Haywood, “Google vs. Bing SEO Key Differences,” SiteProNews, October 23, 2012, available at <http://www.sitepronews.com/2012/10/23/google-vs-bing-seo-key-differences/>; “SEO case study: Sites see more pages indexed by Google than Bing – even post Panda,” Braffton, June 9, 2011, available at <http://www.braffton.com/news/seo-case-study-sites-see-more-pages-indexed-by-google-than-bing-even-post-panda-800527170>.)

⁹⁶ Google’s improvement in providing fresh results is in large part due to a new web indexing system it introduced in June 2010 called “Caffeine.” With Caffeine, Google constantly updates its index of the web in small portions. (See, *e.g.*, Carrie Grimes, “Our new search index: Caffeine,” Google Official Blog, June 8, 2010, available at <http://googleblog.blogspot.com/2010/06/our-new-search-index-caffeine.html>.)

⁹⁷ Saul Hansell, “Google Keeps Tweaking Its Search Engine,” The New York Times, June 3, 2007, available at <http://www.nytimes.com/2007/06/03/business/yourmoney/03google.html?ei=5088&en=f003a2b328ec0a72&ex=1338523200&partner=rssnyt&emc=rss&pagewanted=all>. Bing also detects freshness from signals that do not rely on click-and-query data, such as data it receives from its partnership with Twitter. (Liz Gannes, “Bing — Which Has Deals With Facebook and Twitter — Finally Speaks on Social Search Controversy,” AllThingsD, February 3, 2012, available at <http://allthingsd.com/20120203/bing-which-has-deals-with-facebook-and-twitter-finally-speaks-on-social-search-controversy/>.)

⁹⁸ See, *e.g.*, “How Search Works,” Google - Inside Search, available at <http://www.google.com/insidesearch/howsearchworks/thestory/>; Saul Hansell, “Google Keeps Tweaking Its Search Engine,” The New York Times, June 3, 2007, available at <http://www.nytimes.com/2007/06/03/business/yourmoney/03google.html?ei=5088&en=f003a2b328ec0a72&ex=1338523200&partner=rssnyt&emc=rss&pagewanted=all>.)

⁹⁹ See, *e.g.*, Barry Schwartz, “Google Publishes Its Search Quality Rating Guidelines For First Time,” Search Engine Land, March 1, 2013, available at <http://searchengineland.com/google-publishes-their-search-quality-rating-guidelines-150195>.

¹⁰⁰ See, *e.g.*, “Fighting Spam,” Google - Inside Search, available at <https://www.google.com/insidesearch/howsearchworks/fighting-spam.html>.

56. Microsoft has claimed that it has been particularly hampered by a lack of user data in its ability to offer high-quality results for certain types of queries, including fresh and misspelled queries.¹⁰¹ But one should not confuse poor execution with a lack of scale, especially given that there are many inputs other than user data in providing high-quality services, including engineering talent. In fact, a recent blog post by a Microsoft engineer stated that to be a “viable” search engine requires “not only hiring smart people, but hiring *enough* smart people.” The engineer also noted that “Google’s engineers are amazing,” “[t]here are a limited number of search relevance engineers available,” and “[t]he Bing search relevance staff is a fraction the size of Google’s.”¹⁰² Also, as discussed above, Google has developed superior web crawling and indexing capabilities. Engineering talent and crawling and indexing technology are two of the most important inputs into search quality.

57. In fact, inconsistent with Microsoft’s own claims regarding the relationship between search quality and user data scale, Microsoft now claims to have much better quality than Google. Microsoft’s “Bing It On Challenge” marketing campaign, launched in September 2012, involved users running five searches, comparing Bing and Google search results, and choosing which results they preferred (the identities of the search engines were hidden). Microsoft claims that this “side by side” research showed users preferred Bing search results two to one over Google.¹⁰³ Similarly, Microsoft executive Steve Ballmer publicly stated that 70 percent of the time, there would not be any difference in the quality of Google and Bing search results, that 15 percent of the time Bing’s results would be better, and the remaining 15 percent of the time Google’s results would be better.¹⁰⁴

¹⁰¹ Industry group Fair Search, which Microsoft is a member of, noted that “‘learning by doing’ is a big part of what helps [search] platforms improve.’ This simple fact means that a search engine with fewer searches is less able to innovate as quickly or to provide consumers with as relevant results as a search engine with more searches.” (“Google’s Transformation from Gateway to Gatekeeper: How Google’s Exclusionary and Anticompetitive Conduct Restricts Innovation and Deceives Consumers,” Fair Search White Paper, available at <http://www.fairsearch.org/wp-content/uploads/2011/10/Googles-Transformation-from-Gateway-to-Gatekeeper.pdf>.)

¹⁰² Alex Clemmer, “What ‘viable search engine competition’ really looks like,” January 4, 2014, available at <http://blog.nullspace.io/building-search-engines.html>.

¹⁰³ Microsoft press release, “Bing Challenges Nation to ‘Bing It On,’” September 6, 2012, available at <http://www.microsoft.com/en-us/news/press/2012/sep12/09-06bingchallengepr.aspx>.

¹⁰⁴ Danny Sullivan, “Ballmer: 70% Of The Time, Google & Bing Are The Same, So Try Bing!”, Search Engine Land, October 18, 2011, available at <http://searchengineland.com/ballmer-70-of-the-time-google-bing-are-the-same-so-try-bing-97518>.

58. Other dimensions of quality: There are also many dimensions of quality. Demand by users for a particular online provider does not only depend on the quality of search results or content. Innovative features, an attractive user interface (“UI”), complementary services, speed and ease of use are important quality attributes for online providers.¹⁰⁵ For example, on comparison shopping sites, providing filtering options for modifying results can be an important UI feature for users.¹⁰⁶ Kayak has developed “sliding bars” and other tools to filter query results based on relevant criteria, such as specific departure and arrival times for flights.¹⁰⁷

Complementary services such as same-day delivery from online merchants also can attract users.¹⁰⁸ In search, Google has sought to improve search quality through features including Universal Search, Knowledge Graph, Google Instant (instantaneous display of results while the user types), and Google Suggest (query “autocomplete”). UI improvements in Google search results include the integration of results with maps, local enhancements (*e.g.*, integration with OpenTable), quick answers to common questions (*e.g.*, weather forecasts, sports scores), search refinement options, and mobile-specific UI innovations.¹⁰⁹ These innovations are driven primarily by engineering talent, not a large scale of user data.

59. Distribution arrangements: Online providers also enter into partnerships or distribution arrangements with various parties that can provide access to users.¹¹⁰ The ability of online providers to gain user scale in ways that do not involve user data, including distribution arrangements, further weakens the claimed user data-service quality feedback-loop.

¹⁰⁵ For example, Kayak “routinely work[s] to improve [their] software and algorithms to further reduce the time required to return query results.” (Kayak Software Corporation Q1 2013 10-Q, p. 25.)

¹⁰⁶ David Moth, “14 ways to improve the UX of on-site search results,” Econsultancy, November 13, 2013, available at <https://econsultancy.com/blog/63781-14-ways-to-improve-the-ux-of-on-site-search-results>.

¹⁰⁷ Kayak Software Corporation 2012 10-K, p. 4.

¹⁰⁸ See, *e.g.*, Brad Stone, “Amazon.com Introduces Same-Day Delivery,” *The New York Times*, October 15, 2009, available at http://bits.blogs.nytimes.com/2009/10/15/amazoncom-introduces-same-day-delivery/?_php=true&_type=blogs&_r=0.

¹⁰⁹ “The Story,” Google-Inside Search, available at <http://www.google.com/insidesearch/howsearchworks/thestory/>.

¹¹⁰ See, *e.g.*, Geoffrey A. Manne and William Rinehart, “The Market Realities that Undermined the FTC’s Antitrust Case Against Google,” *Harvard Journal of Law & Technology Occasional Paper Series* — July 2013, p. 15, available at <http://jolt.law.harvard.edu/antitrust/articles/ManneRinehart.pdf>: “One common refrain from Google’s critics is that Google’s access to immense amounts of data used to increase the quality of its targeting presents a barrier to competition that no one else can match, thus protecting Google’s ‘unassailable’ monopoly. But scale comes in many ways. In the first place, data can be bought; there’s plenty out there, and lots of it is for sale.”

60. In 2009, for example, Microsoft entered into a partnership to provide search results and search advertisements to Yahoo!.¹¹¹ This partnership more than doubled Microsoft's user scale when the partnership became fully operational in August 2010.¹¹² Microsoft also has obtained distribution of its search service through various desktop search distribution channels. Microsoft has entered into distribution arrangements with computer OEMs that sell roughly 70 percent of all U.S. personal computers.¹¹³ It also has entered into a distribution deal with one of the largest distributor of custom toolbars, Conduit (now called Perion),¹¹⁴ and some of the largest independent software vendors, including Oracle and Skype (which Microsoft acquired in 2012).¹¹⁵ In the browser channel, Microsoft's Internet Explorer (the majority of which come with Bing as the default search engine) is one of the most widely used Internet browsers in the U.S., with a 36 percent share on desktop computers.¹¹⁶ Google also has competed for

¹¹¹ See, e.g., David Goldman, "Microsoft and Yahoo: Search partners," CNN Money, July 29, 2009, available at http://money.cnn.com/2009/07/29/technology/microsoft_yahoo/: "This deal is really about scale," said Yahoo Chief Executive Carol Bartz on a conference call."

¹¹² According to comScore, Yahoo! had about 2.7 billion user queries on its sites in August 2010, while Microsoft had 1.7 billion. (comScore press release, "comScore Releases August 2010 U.S. Search Engine Rankings," September 16, 2010, available at http://www.comscore.com/Insights/Press_Releases/2010/9/comScore_Releases_August_2010_US_Search_Engine_Rankings.)

¹¹³ Gartner PC Shipment Data (U.S.), 2013.

¹¹⁴ Ronen Shilo, "Bing – It has a nice 'ring' to it," Conduit, December 1, 2010, available at <http://blog.conduit.com/2010/12/01/bing-it-has-a-nice-ring-to-it-2/>; Matt Rosoff, "Toolbar Maker Dumps Google for Bing," Business Insider, December 1, 2010, available at http://articles.businessinsider.com/2010-12-01/tech/30050901_1_toolbars-microsoft-s-bing-conduit. Conduit accounts for approximately 10 percent of Bing's total U.S. searches. (Zvi Boimer and Matan Benjamin, "Perion Network Ltd. Assigned 'ilA-' Rating; Outlook Is Stable", Standard & Poor's Maalot, March 6, 2014, available at <http://www.perion.com/wp-content/uploads/2014/03/Perion-ENG.pdf>; Conduit press release, "Perion & Conduit's 'Client Connect' Combine to Create Industry Leader," September 16, 2013, available at <http://www.conduit.com/pressrelease/item/perion--conduits-client-connect-combine-to-create-industry-leader>.)

¹¹⁵ In a 2008 press release following Microsoft's agreement with Oracle, Microsoft noted that "Java is one of the most widely available and popular software platforms. It is already present on 91 percent of Internet-connected PCs worldwide. The Java Runtime Environment is one of the highest-volume consumer downloads on the Web, with tens of millions of downloads each month..." (Microsoft press release, "Sun Microsystems to Distribute Microsoft Live Search-Powered Toolbar as Part of Java Runtime Environment," November 10, 2008, available at <http://www.microsoft.com/presspass/press/2008/nov08/11-10livejrempr.msp>.) Google lost the distribution arrangement with Sun Microsystems after Sun merged with Oracle and Microsoft entered into a deal with Oracle. Also see, Microsoft press release, "Microsoft to Acquire Skype," May 10, 2011, available at <http://www.microsoft.com/presspass/press/2011/may11/05-10corpnewspr.msp>; Liz Tassej Gerber, "Bing and Skype – Better Together," Bing Blogs, March 27, 2012, available at http://www.bing.com/community/site_blogs/b/search/archive/2012/03/27/bing-and-skype-better-together.aspx.

¹¹⁶ "Top 5 Desktop Browsers in the United States on July 2014," StatCounter Global Stats, available at <http://gs.statcounter.com/?PHPSESSID=2ueacvaftolkco8m78dekippee7#desktop-browser-US-monthly-201407-201407-bar>.

distribution for its search engine. Other types of online providers also invest in distribution to obtain access to users.¹¹⁷

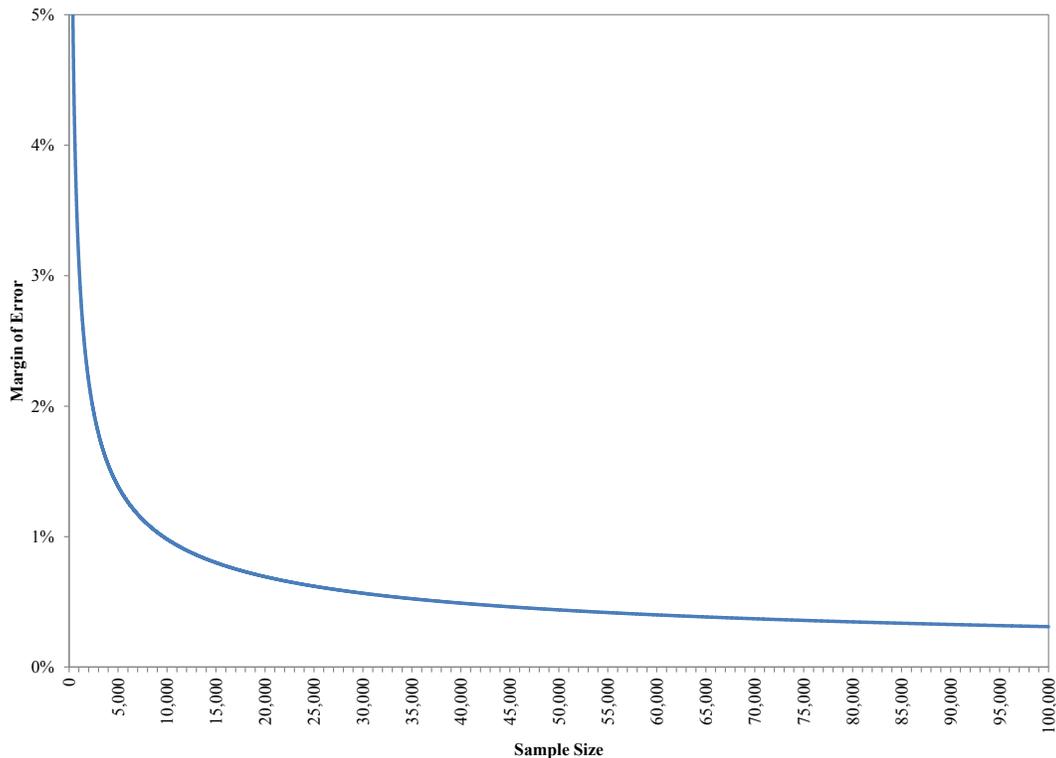
C. Because of rapidly diminishing returns to user data, any advantages of scale generally weaken or even disappear at a low level

1. Diminishing returns in the provision of user services

61. In the provision of many online services, as in almost any business, there are benefits of scale, but these benefits are subject to diminishing returns. To illustrate the concept of diminishing returns to scale in statistical terms, consider the statistical sampling error when performing a survey. The survey sampling error decreases as more people are surveyed, but the rate of decrease slows as the sample size gets larger. A survey with a random sample of 1,000 respondents has a maximum margin of sampling error of approximately 3 percentage points at a 95 percent confidence level. This means that 95 percent of the time, the survey would give rise to reported results within 3 percentage points of the true value. Increasing the scale of the sample by 1,000 respondents would reduce the margin of error by 0.9 percentage points (to about 2.2 percent). However, for a survey with 10,000 respondents, increasing the sample size by 1,000 yields a decline in the margin of error of only 0.05 percentage points. For a survey with 100,000 respondents, increasing the sample size by 1,000 yields a decline in the margin of error of only 0.002 percentage points. Figure 2 below illustrates that the margin of sampling error (measured on the vertical axis) declines with sample size (measured on the horizontal axis), but the rate of the decline diminishes rapidly.

¹¹⁷ For example, Yelp has a deal with T-Mobile to have the Yelp app preloaded on certain mobile devices. (“Yelp Adds Saved-Search Function, New Search Filters – But Only for App on Select T-Mobile Phones,” Launch Media, November 2, 2011, available at <http://blog.launch.co/blog/yelp-adds-saved-search-function-new-search-filters-but-only.html>.)

Figure 2: Diminishing Returns to Scale—Sampling Error and Sample Size



62. The statistical example above is obviously simplistic, but a similar concept of diminishing returns generally applies to the utilization of user data collected by online firms. For instance, the value of user data in returning relevant results to user search queries is subject to diminishing returns. Most user data collected and utilized by search providers involves information about the search terms users have entered previously, and which results they have clicked on, if any. This information allows search providers to gain insight into what results may be relevant in response to particular search terms, and thereby return more relevant results to users. Click-and-query data are an important input into search algorithms, but the value of incremental data in providing relevant search results decreases as the amount of data available to those algorithms increases. Returns to user data scale diminish rapidly for common queries, referred to as “head” queries, which are queries entered frequently by users. A large share of head queries include navigational queries, which are queries that users enter on search engines with the intent to navigate to the website of a particular online provider, such as “Facebook” or

“Amazon.”¹¹⁸ Other types of head queries include popular products (e.g., “Xbox”), personalities (e.g., “Angelina Jolie”), or notable events (e.g., “World Cup”). The marginal value of additional head queries is likely to be minimal, or even zero, at a very low scale for a search provider. For instance, a search provider that has data on user clicks for 10,000 previous queries for “Facebook” or “Amazon” is likely to be able to determine the most relevant search results as well as a provider that has seen that same query 100,000 times. Thus, it is generally accepted that significant user scale is not necessary to provide relevant search results for more popular queries.

63. It has been argued that economies of scale in returning relevant search results are especially important for queries that are infrequently entered by users, referred to as “tail” queries. Tail queries include misspelled queries, addresses, specific product descriptions or model numbers, and detailed queries composed of multiple terms.¹¹⁹ For some tail queries, there can be value to having a greater amount of user click and query data, since this information may contain data for the same tail queries. A search provider with small scale may have no data on user clicks in response to the same or similar queries previously entered by users. In contrast, a larger provider may have an advantage over smaller providers to the extent that it has seen the same (or similar) tail query before.

64. However, an increase in query volume has not eliminated or materially reduced the portion of Google’s traffic that is comprised of queries that it has never seen before. According to Google, in 2013 “[e]very single day 15 percent of the questions people ask of Google are questions we’ve never seen before.”¹²⁰ This percentage has not declined significantly since 2007,¹²¹ while during this time period (2007 to 2013), Google’s total U.S. query volume almost

¹¹⁸ See, e.g., Matt Tatham, “Facebook was the top search term in 2012 for fourth straight year,” Hitwise Experian, December 20, 2012, available at <http://www.experian.com/blogs/marketing-forward/2012/12/20/facebook-was-the-top-search-term-in-2012-for-fourth-straight-year/>.

¹¹⁹ See, e.g., Jayson DeMers, “The Resurgence of Long-Tail Keywords in SEO,” Search Engine Watch, March 18, 2013, available at <http://searchenginewatch.com/article/2255280/The-Resurgence-of-Long-Tail-Keywords-in-SEO>.

¹²⁰ Julie Bort, “Nearly 500 Million Searches A Day Are For Things Google Has Never Heard Of,” Business Insider, May 13, 2013, available at <http://www.businessinsider.com/500m-things-google-has-never-heard-of-2013-5#!CdFSB>.

¹²¹ Dan Farber, “Google Search scratches its brain 500 million times a day,” CNET, May 13, 2013, available at <http://www.cnet.com/news/google-search-scratches-its-brain-500-million-times-a-day/>: “On a daily basis, 15 percent of queries submitted -- 500 million -- have never been seen before by Google’s search engine, and that has continued for the nearly 15 years the company has existed, according to John Wiley, the lead designer for Google

tripled.¹²² Having greater query volume therefore does not eliminate a platform’s need to return relevant results to queries that it has never seen before. Indeed, as I discuss above, providing relevant results in response to tail queries such as misspellings, including queries never seen before, involves clever engineering and the use of other types of data.¹²³

65. Thus, both for head queries and tail queries, there is diminishing marginal value of user data scale.¹²⁴ Diminishing returns to scale mean that the benefits from additional scale (either in attaining lower costs or higher quality) become progressively smaller as query volume increases. As a result, any competitive advantage that a larger rival has over smaller rivals also diminishes rather than strengthens as the industry grows. In fact, in some cases, such as with “head” search queries, there may be zero marginal value of incremental query volume after a certain scale. Thus, any advantage of size may disappear at a fairly low scale and, as the industry grows, larger providers may have no advantage at all relative to smaller rivals.¹²⁵ Moreover, because of diminishing returns to scale, the value of incremental users is greater for smaller rivals than it is for a larger platform, which means that smaller rivals may have greater incentive to compete in attracting users at the margin, such as by investing in quality or distribution.

Search.” See also, Sean Ammirati, “Google’s Udi Manber – Search is a Hard Problem,” readwrite, June 21, 2007, available at http://readwrite.com/2007/06/21/udi_manber_search_is_a_hard_problem.

¹²² comScore press releases; Total Core Search (2007) and Explicit Core Search (2013).

¹²³ For example, a search engine’s ability to return the best results for a query comprised of a specific product model number may have nothing to do with whether another user previously had conducted the same search query. Instead, it would most likely depend on whether the search engine had “crawled” web pages containing the exact model number queried by the user, or obtained product data feeds from manufacturers or retailers, inputs which are independent of the search provider’s volume of user data.

¹²⁴ A study by Lesley Chiou and Catherine Tucker supports the existence of rapidly diminishing returns to scale in the utilization of user data for the provision of search results. In particular, the authors analyze how the amount of query data available to search engines affects search quality by examining user behavior around the times search engines changed their log retention policies (*i.e.*, began keeping less historical click and query data). The authors find that there is “little empirical evidence that reducing the length of storage of past search engine searches affected the accuracy of search. Our results suggest that the possession of historical data confers less of a competitive advantage than is sometimes supposed.” (See, *e.g.*, Lesley Chiou and Catherine Tucker, “Search Engines and Data Retention: Implications for Privacy and Antitrust,” MIT Sloan Research Paper No. 5094-14, May 27, 2014, p. 1.)

¹²⁵ However, a second effect may offset the first to some extent. Even if market shares stay the same as the industry grows, the *absolute* difference in scale between a large provider and smaller rivals grows. Thus, while the marginal value of the additional user data to the large provider diminishes with scale, the fact the absolute size of the large provider increases relative to the smaller rival may increase the advantage of the larger provider.

2. *Diminishing returns in monetization*

66. Significant economies of scale also are claimed to arise from a monetization feedback loop—*i.e.*, that the more users an online platform has, the more user data it can collect, the better it can target ads to users, and the more effectively it can monetize the site.¹²⁶ It is claimed that the inability to monetize search effectively due to lower user scale hampers the ability of rivals to compete for users because the reduction in advertising revenues deprives it of the ability and incentive to make investments in improving quality. As Nathan Newman argues with regard to Google:

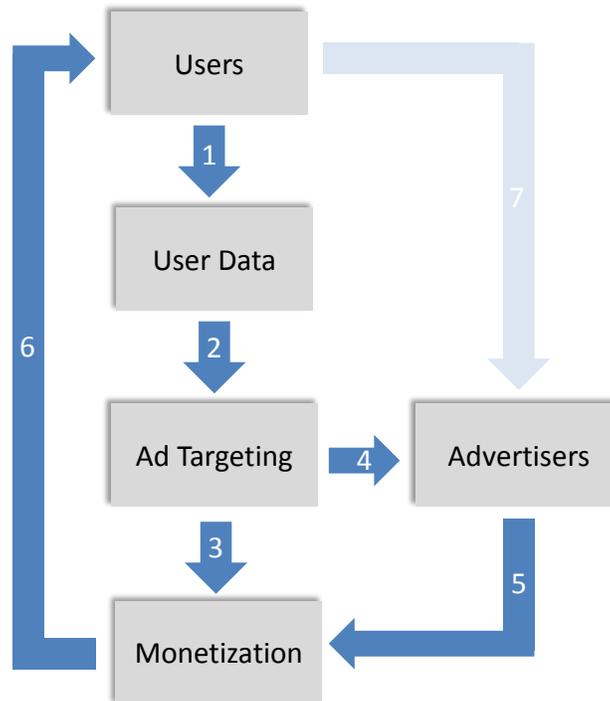
any competitor to Google has to pay the fixed costs of setting up a competing service not only with fewer initial users but making far less per user clicks on ads as well. And since advertisers want a company with enough customers to generate broad data to help in targeting ads, you have a chicken-and-egg cycle creating barriers to entry that only antitrust intervention will likely solve.¹²⁷

67. There are two possible theories why a platform with more users may be able to better monetize its services and, in turn, better compete for users. First, having more users may allow a platform to collect more user data (step 1 in Figure 3 below), which may enhance the platform's ability to target ads to users (step 2). Better ad targeting presumably increases monetization directly by increasing the propensity of users to click on ads (3) and indirectly by increasing demand from advertisers (4), which increases the number of ads and the cost-per-click that advertisers pay (5). In turn, better monetization supposedly allows a search platform to better compete for users by enabling the platform to make investments in improving quality (6). The second theory is that a greater number of users itself may increase demand by advertisers (7). I address in Section IV. C below because it does not focus on the value of user data, but rather, on cross-platform network effects between users and advertisers.

¹²⁶ Nathan Newman, "Search, Antitrust and the Economics of the Control of User Data," working paper, last revised August 14, 2014, NYU Information Law Institute, p. 17, forthcoming 40(3) *YALE J. REG.* (2014).

¹²⁷ Nathan Newman, "Taking on Google's Monopoly Means Regulating its Control of User Data," Huffington Post, September 24, 2013, available at http://www.huffingtonpost.com/nathan-newman/taking-on-googles-monopol_b_3980799.html.

Figure 3: Claimed Monetization Feedback Loop



68. I discuss economies of scale in monetization in the context of search ads, but similar economics apply to other types of online ads. As I discuss, the claim that the collection of data from users leads to significant economies of scale in monetization, and thereby also leads to tipping toward a dominant platform, is misguided as a matter of economics and empirical evidence.

69. For starters, it is important to understand that, to a large extent, advertisers target their own ads. For instance, in the context of search advertising, advertisers target their ads by choosing keywords, by selecting how closely user search terms must match those keywords in order for their advertisement to potentially be shown to users (*e.g.*, keyword match types),¹²⁸ and by electing their bids (referred to as the maximum cost-per-click). Geo-locational and time scheduling selection also are used by advertisers to more narrowly target ads to users.¹²⁹

¹²⁸ See, *e.g.*, Google AdWords Help, “Using keyword matching options,” available at <http://support.google.com/adwords/bin/answer.py?hl=en&answer=6100>.

¹²⁹ For instance, Twitter allows advertisers to “target Promoted Tweet and Promoted Account campaigns based on user geography.” (Twitter Inc. 2013 10-K, p. 10.) Advertisers also may select the time and/or day of the week their ads are shown. (Google AdWords Help, “Using custom ad scheduling,” available at <https://support.google.com/adwords/answer/2404244?hl=en>.)

70. It is claimed that there are significant economies of scale in monetization due to the value of having large amounts of user data for purposes of targeting ads. It is also argued that these economies of scale are reflected in higher cost-per-click (CPC) to advertisers and higher revenue-per-thousand queries (RPM) for large search platforms.¹³⁰ However, from a theoretical perspective, the effect of increased user volume on RPM (or CPC) is ambiguous.¹³¹ This is because there is an economic effect that tends to *reduce* RPM as a platform’s volume of users increases. In particular, an increase in the number of user queries corresponds to an increase in the supply of ad slots that the platform can offer advertisers, which can lower the resulting prices of ads, and therefore reduce RPM.¹³² Fundamental economic principles indicate that, all else equal, an increase in supply leads to lower price when demand is downward-sloping.¹³³ As the number of queries increases, the incremental value of an ad slot to advertisers, and their willingness-to-pay for the ad slot, may decrease. The lower willingness-to-pay means that advertisers will bid less on keywords as the number of ad slots increases, which can lead to a lower average CPC or lower ad impressions per query (APQ) for the platform. As a result, RPM may decrease with increased scale of users.¹³⁴

71. This discussion does not suggest that there are no economies of scale in monetizing at *any* query scale. When a platform is small, the positive effects of user data can overcome the

¹³⁰ See, e.g., Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, last revised August 14, 2014, NYU Information Law Institute, p. 5, forthcoming 40(3) YALE J. REG. (2014): Google “is able to charge a far higher price to advertisers for each ‘click’ on an ad with strong evidence indicating that higher ‘cost per click’ is due to the overwhelming control of user data Google has.”

¹³¹ Note that CPC and RPM are related. In particular, $RPM = (APQ \times CTR \times CPC) \times 1000$, where CPC is the dollar amount that advertisers pay on average for each click on an ad impression (\$/click); CTR is the click-through rate, which is the average number of clicks per ad impression (clicks/impression); and APQ is the ads-per-query, which is the average number of ad impressions per search query (impressions/query). Because RPM is a more complete measure of a provider’s monetization than CPC, I generally discuss the role of user data in increasing RPM rather than CPC.

¹³² For general search engines, advertisers purchase ad space on queries through an auction (in the case of Google and Bing, serviced through the Google AdWords or the Microsoft adCenter systems, respectively). If advertisers bid successfully, they appear on the search result page for a given user query (referred to as an ad impression).

¹³³ Advertisers are likely to have a downward sloping demand for search ad space on a particular search platform especially if the increased query volume comes, at least in part, from an increase in queries per user, which raises the probability that an ad will be shown to the same user multiple times. Generally, there is diminishing value to showing ads repeatedly to the same customer. The diminishing value of incremental queries is particularly pronounced for advertisers with limited budgets—as the number of queries increases those limited budgets are spread out over more auctions.

¹³⁴ It is also incorrect to assume that additional queries are just as valuable as existing queries. Incremental queries may be less commercial than existing queries, which could reduce the average RPM.

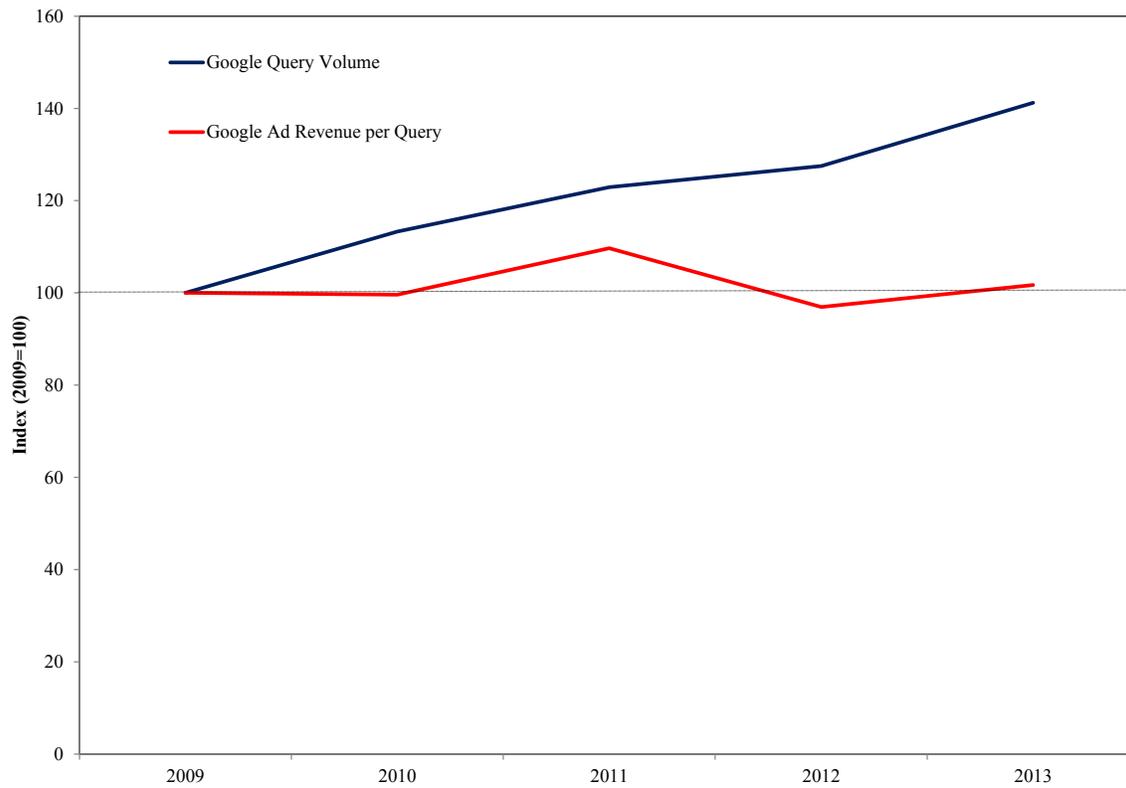
diminishing marginal value to advertisers of incremental ad slots. In particular, for a small platform, user data volume may play an important role in training the ad-targeting systems, and thereby in attracting advertisers.¹³⁵ However, there are diminishing returns to scale in these regards, and these effects are likely small or nonexistent for larger platforms. Moreover, the decreasing marginal value to advertisers of additional advertising slots is likely to become more significant as a platform grows. Thus, it is possible that for large platforms, the effects of the downward slope of advertising demand more than offsets any outward shift in the demand curve due to improved targeting.

72. While the effect of scale on monetization is ambiguous, the empirical evidence does not support the claim that higher user scale necessarily leads to better monetization. In the context of general search, there is no evidence that greater search query volume leads to higher RPM for established search providers. Figure 4 below shows the relationship between Google's U.S. query volume and the revenue Google derives from search ads shown on Google sites in the U.S. during the past five years (2009 to 2013).¹³⁶ As the figure indicates, while Google's query volume has increased by over 40 percent since 2009, its RPM has not increased at all.

¹³⁵ The effect of incremental advertisers on search monetization also is subject to diminishing returns. This is so because, particularly for platforms with a significant number of advertisers, the incremental revenue from a new advertiser tends to be less than its ad spend because additional advertisers "crowd out" other advertisers on the platform. First, because there is a maximum number of ad slots on a search result page, for "fully-sold" auctions (*i.e.*, auctions for which all ad slots on a search result page are filled by ads), successful bids by additional advertisers will displace the ads of other advertisers. Even in auctions that are not "fully-sold," the presence of additional successful bidders decreases the probability that users will click on other ads on the page (*i.e.*, decreases the expected CTR of other ads). Accordingly, search-user clicks on ads tend to increase less than proportionately with an increase in the number of advertisers. These quantity effects can be offset by the fact that additional advertisers can increase the CPC paid for higher ad placement because the CPC paid by each advertiser is based in part on the bid of the next highest ranked ad in the auction. Additional advertisers also can lead to higher CPC paid by ads in lower positions by changing the bidding strategies of those advertisers.

¹³⁶ comScore. Total Core Searches are used before June 2010, when comScore began reporting Explicit Core Searches; Explicit Core Searches are used from June 2010 to January 2014. Google's query volume reflects U.S. user queries performed on Google.com and other Google-branded sites (*e.g.*, Google News) using computers at home and at work (*i.e.*, excluding mobile searches). Google's U.S. search ad revenues associated with this query volume are estimated using information from Google's financial statements, and from industry analysts. These financial statements also provide the share of total Google revenue generated in the U.S.; this share is assumed to be constant across all Google revenue sources. Google's financial statements provide quarterly advertising revenues by source, including "Google" sites. I exclude display ad revenue from Google site YouTube. Estimated YouTube gross ad revenues from eMarketer are available beginning in 2010. (Tim Worstall, "Google's YouTube Ad Revenues May Hit \$5.6 Billion In 2013," *Forbes*, December 12, 2013, available at <http://www.forbes.com/sites/timworstall/2013/12/12/googles-youtube-ad-revenues-may-hit-5-6-billion-in-2013/>.) I also exclude mobile ad revenues. Analyst-reported estimates of Google's annual mobile ad revenue for 2010 through 2012 are used to estimate Google's U.S. advertising revenue from non-mobile sources, assuming that Google's mobile ad revenue in 2013 was identical to 2012. (Phil Goldstein, "Google: Mobile business worth \$1B in

Figure 4: Google U.S. Query Volume and Ad Revenue per Query on Google Sites



73. Some commentators point to the alleged existence of a large gap between Microsoft’s and Google’s RPM and CPC as evidence of Microsoft’s inability to monetize search as effectively as Google due to a lack of user scale.¹³⁷ However, there is no publicly-available information with which to reliably compare Google and Bing’s RPM.¹³⁸ Moreover, the key

revenues annually,” Fierce Wireless, October 14, 2010, available at <http://www.fiercewireless.com/story/google-mobile-business-adding-1b-revenue/2010-10-14>; Greg Sterling, “What To Make Of Google’s \$8 Billion ‘Mobile Run Rate’ Figure,” Marketing Land, October 19, 2012, available at <http://marketingland.com/what-to-make-of-googles-8-billion-mobile-run-rate-figure-24422>.)

¹³⁷ Nathan Newman states, for example, that “Google receives an extremely high premium cost per click (CPC). One advertising analyst estimated that for the same keywords, the ‘average CPC on Bing is somewhere around 1/4 or 1/5 of our average CPC on Google.’ Another found that on specific search terms, CPC rates on Bing were slightly higher but still were discounted 49% to 71% compared to Google, while others estimate that the CPC rate is 20% to 40% lower on Bing.” (Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, last revised August 14, 2014, NYU Information Law Institute, p. 25, forthcoming 40(3) YALE J. REG. (2014).)

¹³⁸ A chart below utilizes an estimate of Google’s RPM based on the company’s financial statements, and query data from comScore. However, Microsoft’s own financial statements do not provide enough detail to reliably estimate the portion of the firm’s Online Services Division revenue that comes from search ad revenue on Microsoft/Yahoo! sites (*i.e.*, excluding display ad revenue and syndicated search advertising revenue).

question is not whether effective targeting leads to better monetization, but whether greater user scale leads to better monetization. There is no basis to conclude that if a particular site achieves a higher RPM than rivals, it is due to greater user scale. Monetization is affected by many factors including, importantly, engineering efforts to improve ad-targeting technologies and other investments.¹³⁹

74. A natural experiment suggests that any shortcomings in Microsoft’s monetization is due to inferior engineering of its ad-targeting technologies, not a lack of query volume. In particular, Bing’s deal to serve search advertisements on the Yahoo! platform essentially doubled Bing’s query volume in August 2010. Advertisers could reach Bing and Yahoo! users by advertising on one ad platform (adCenter), and Bing had access to Yahoo! click-and-query data for ad targeting. If claims regarding the effects of scale on RPM were correct, Microsoft should have increased its own monetization, as well as Yahoo!’s. However, Yahoo!’s monetization is reported to have *worsened* after Microsoft began serving ads on its site. Yahoo!’s then-CEO, Carol Bartz, attributed Yahoo!’s decline in search revenue to poor performance by Microsoft, stating that “adCenter isn’t yet producing the RPS [revenue per search] we hoped for and are confident as [sic] possible... technical limitations in the current adCenter platform mean the click volumes just isn’t [sic] there yet.”¹⁴⁰

75. Lastly, even if rivals were not able to monetize as effectively until they gained greater user scale, it is not clear that this would impede their ability to compete. In theory, lower monetization could either inhibit rivals’ *ability* or *incentive* to invest in quality improvements.¹⁴¹

¹³⁹ Furthermore, the type of user search being conducted affects monetization, as more commercially-oriented queries (*e.g.*, “buy TV”) reflect higher user intent to purchase, and therefore are more valuable to advertisers.

¹⁴⁰ Bartz also stated that “[w]e are working very close [sic] with Microsoft on this. They understand the issues and they’re hard at work on systems architecture, science models and better features and functions in adCenter. They have an aggressive roadmap to bring those to the marketplace.” (Danny Sullivan, “The Yahoo Search Revenue Disaster,” Search Engine Land, April 20, 2011, available at <http://searchengineland.com/the-yahoo-search-revenue-disaster-73868>.) Two years later, in 2013, it appeared that Microsoft’s contribution to Yahoo!’s search ad revenue continued to lag, according to Yahoo! CFO Ken Goldman: “There was still a gap in monetization and we will work with Microsoft to improve our search monetization.” (Danny Sullivan, “Why Yahoo Will Never Reach The ‘Revenue Per Search’ That Microsoft Promised,” Marketing Land, May 7, 2013, available at <http://marketingland.com/yahoo-microsoft-rps-guarantee-42680>.)

¹⁴¹ Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, last revised August 14, 2014, NYU Information Law Institute, p. 26, forthcoming 40(3) YALE J. REG. (2014): “lower revenue has to cover much of the same fixed costs as Google for maintaining a competitive search advertising platform illustrates the major barrier to entry for existing or potential challengers to Google that make its monopoly unlikely to lessen based only on market forces.”

With regard to the financial *ability* to invest, there are many online providers that possess ample financial resources to invest in improving their products and services. For example, Apple currently has well over \$100 billion in cash, nearly 10 percent of all corporate cash held by nonfinancial companies.¹⁴² Additionally, there are many outside means through which online providers can attain funding to grow their businesses, including venture capital firms, “angel” investors, and IPOs.¹⁴³

76. The second argument is that user scale diminishes *incentives* to invest in quality because the fixed costs of investment are spread across a smaller user base.¹⁴⁴ This argument is incorrect. Investment incentives depend on *marginal* effects, not average effects. Consider the marginal effects of an increase in quality. Because the price of most online services to users is zero, the benefits of increased quality to a platform come in the form of increased user activity, which increases the amount of advertising available for sale by the platform.¹⁴⁵ There is no sound economic basis for assuming that the *incremental* user volume due to a given quality investment is greater for a larger platform than a smaller one. For example, if the smaller platform has fewer users because it currently has lower search quality, then an investment in increased quality might attract more incremental users than would the same investment made by the larger platform. As a general matter, a smaller platform could well have greater incentives to invest in quality improvements than a larger platform.

¹⁴² Emily Chasan, “Apple Now Holds 10% of All Corporate Cash: Moody’s,” The Wall Street Journal, October 1, 2013, available at <http://blogs.wsj.com/cfo/2013/10/01/apple-now-holds-10-of-all-corporate-cash-moodys/>.

¹⁴³ See, e.g., Heather Somerville, “Silicon Valley tech companies reap record-level investments,” San Jose Mercury News, April 18, 2014, available at http://www.mercurynews.com/business/ci_25590584/valley-companies-reap-record-level-investments.

¹⁴⁴ Newman claims that “the total number of click-throughs (Clicks) generated by an advertising platform times the average Cost Per Click (CPC) charged to those advertisers must yield revenue more than the platform’s fixed costs (FixedCosts). Any challenger to Google would have to generate some combination of CPC rates times total clicks by users to generate revenue to cover those fixed costs to even begin to be a competitive challenge to Google -- and the fact that Microsoft with nearly half the user base of Google still generated \$2.6 billion in losses compared to its costs shows how high that competitive barrier is.” (Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, last revised August 14, 2014, NYU Information Law Institute, pp. 27-28, forthcoming 40(3) YALE J. REG. (2014).)

¹⁴⁵ In the context of search, search-quality improvements could even reduce the volume of advertising because users may substitute clicking on unsponsored search results for clicking on ads.

IV. Online Markets Have Not “Tipped” to Dominant Online Platforms

A. There is no evidence that online markets have tipped to dominant platforms

77. Contrary to claims that online markets are prone to “tip” to dominant platforms because of the collection of user data, the relatively short history of the Internet is filled with examples of “dominant” platforms or providers that subsequently were displaced by new firms—many new entrants have prospered, and many large online providers thought to be dominant at the time have failed or declined in the face of new competition:

- In the social network area, MySpace was once the clear leader among social networking sites, with first-mover advantage over many rival social media sites, and the backing of News Corporation.¹⁴⁶ However, the prominence of Myspace as a social network has now faded dramatically.¹⁴⁷ It was replaced by a new entrant, Facebook, which is currently the top social networking site in terms of users by a large margin.¹⁴⁸ MySpace itself displaced another leading social network, Friendster, which was “once the hottest thing in social networking.”¹⁴⁹
- In the late 1990s, GeoCities was a top-five Internet site that allowed users to design personal web pages. It was acquired by Yahoo! in 1999 for about \$3 billion. However, it closed down in 2009, and has been replaced largely by social networking services like Facebook and blogging services like WordPress.¹⁵⁰

¹⁴⁶ See, e.g., Adam Hartung, “How Facebook Beat MySpace,” *Forbes*, January 14, 2011, available at <http://www.forbes.com/sites/adamhartung/2011/01/14/why-facebook-beat-myspace/>. MySpace launched in August 2003, and by 2005 was third most popular website in the U.S. (Sean Smith, “The rise and fall of MySpace,” *Financial Times*, February 11, 2010, available at <http://www.ft.com/cms/s/0/f42faf78-172f-11df-94f6-00144feab49a.html>.)

¹⁴⁷ Matthew Garrahan, “The rise and fall of MySpace,” *Financial Times*, December 4, 2009, available at <http://www.ft.com/cms/s/2/fd9ffd9c-dee5-11de-adff-00144feab49a.html>; Brennon Slattery, “After Numerous Shake-Ups, is MySpace Dying?” *PC World*, February 23, 2010, available at http://www.pcworld.com/article/190034/after_numerous_shakeups_is_myspace_dying.html.

¹⁴⁸ Jennifer Saba, “Facebook reveals daily users for U.S. and UK, data aimed at advertisers,” *Reuters*, August 13, 2013, available at <http://www.reuters.com/article/2013/08/13/us-facebook-users-idUSBRE97C0WY20130813>.

¹⁴⁹ Robert McMillan, “The Friendster Autopsy: How a Social Network Dies,” *Wired*, February 27, 2013, available at <http://www.wired.com/2013/02/friendster-autopsy/>.

¹⁵⁰ “GeoCities' time has expired, Yahoo closing the site today,” *Los Angeles Times*, October 26, 2009, available at <http://latimesblogs.latimes.com/technology/2009/10/geocities-closing.html>; Stephen Shankland, “Now closing: GeoCities, a relic of Web's early days,” *CNET*, April 23, 2009, available at <http://news.cnet.com/now-closing-geocities-a-relic-of-webs-early-days/>.

- Blogger, launched in 1999, was one of the first blogging tools available, and was very popular through the mid-2000s (Google purchased it in 2003).¹⁵¹ Competing blog service provider WordPress, launched in 2003, has grown rapidly to surpass Blogger, and is now the world's leading blogging platform, powering roughly one of every six Internet sites.¹⁵²

This history illustrates that success can be very temporary and even seemingly unassailable incumbents can quickly be replaced by firms with better products.

78. In the online search category, new search firms with differentiated business models have entered are replaced incumbents. Yahoo!, Lycos, and AltaVista were all thought to be dominant, entrenched search providers, but lost their positions as the most successful search engines. The following statements were made about these providers:

- Lycos (1994): “Lycos appears to be the strongest system overall. It offers comprehensive coverage of the WWW, an efficient indexing scheme, and impressive search and display features.”¹⁵³
- Yahoo! (1994): “... the contest to become the dominant search engine is close to over, with Yahoo being the winner...”¹⁵⁴ “Certainly Yahoo! is the leader of the search engines.”¹⁵⁵ “The problem of selection is particularly acute for Yahoo! since it has a near-monopoly of the hierarchical directory search market.”¹⁵⁶ “Yahoo! ... the most successful company ever spawned by the World Wide Web. [...] This much is

¹⁵¹ Preston Gralla, “Blogging service shootout: Blogger vs. WordPress,” Computerworld, March 13, 2012, available at http://www.computerworld.com/s/article/9224441/Blogging_service_shootout_Blogger_vs_WordPress. In 2007, for instance, it was a top-20 site, as measured by unique users. (Compete data for September 2007, available at <https://blog.compete.com/2007/10/30/top-50-websites-domains-digg-youtube-flickr-facebook/>.)

¹⁵² J. J. Calao, “With 60 Million Websites, WordPress Rules The Web. So Where's The Money?” Forbes, September 24, 2012, available at <http://www.forbes.com/sites/jjcolao/2012/09/05/the-internets-mother-tongue/>.

¹⁵³ Stacey Kimmel, *Robot-generated Databases on the World Wide Web*, 19(1) DATABASE 40 (February 1996).

¹⁵⁴ Mark Veverka, “Merger Mania Has Finally Penetrated the Internet Space,” The San Francisco Chronicle, June 24, 1998.

¹⁵⁵ Paul Cook, Portfolio Manager Munder Netner Fund, speaking on CNN MoneyWeek, June 14, 1998, Transcript # 98061400V35.

¹⁵⁶ Jack Schofield, “Computing and the Net: The new seekers,” The Guardian, November 6, 1997.

clear: Yahoo! has won the search-engine wars and is poised for much bigger things.”¹⁵⁷

- AltaVista (1995): AltaVista, called the “‘Google of Its Time’ ... appeared on the search engine scene in December 1995 ... indexing around 20 million web pages, at a time when indexing 2 million web pages was considered to be big” and was a “darling of reviews and word-of-mouth praise.”¹⁵⁸

79. Google did not become the most popular search engine as a result of access to large amounts of user data. In fact, when Google first started, it had no user data. Even Google’s critics acknowledge that Google earned its current competitive position through innovation and clever engineering. Google’s main initial innovation was the PageRank algorithm, devised by its founders, which analyzes the number of sites which link to potentially relevant sites (and the sites that link to those sites), as a way to determine the quality and relevancy of websites.¹⁵⁹ This innovation, which did not require user data, was one of the key factors that helped Google succeed as a new entrant that faced multiple established search engines. Google certainly did not become a successful search engine through the collection of user data (or by invading user privacy), as some commentators claim.

80. It has been argued that, while there are several examples of new entrants overtaking large incumbents in the early days of the Internet, the era of “big data” has led to large incumbents such as Google, Facebook, and Amazon becoming entrenched, and maintaining high shares for a long period of time. Although some of these providers now have been successful for several years, this does not mean that they have become entrenched as dominant platforms. Not even the most ardent critics of these online providers can claim that these providers face little competitive constraint and are “resting on their laurels.”

81. Amongst providers of general search, there is no sign that the market is “tipping” towards Google. Figure 5 below shows the share of U.S. general search queries for Google, Bing,

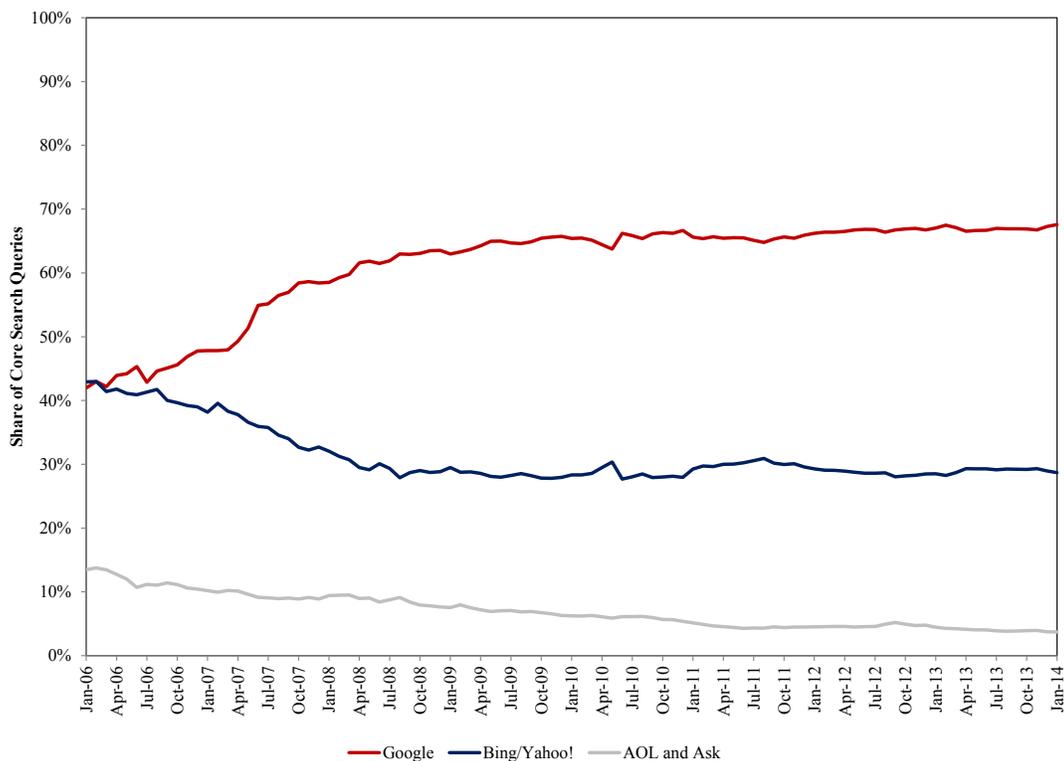
¹⁵⁷ Randall E. Stross, “How Yahoo! Won the Search Wars,” *Fortune*, March 2, 1998, available at http://archive.fortune.com/magazines/fortune/fortune_archive/1998/03/02/238576/index.htm.

¹⁵⁸ Danny Sullivan, “A Eulogy For AltaVista, The Google Of Its Time,” *Search Engine Land*, June 28, 2013, available at <http://searchengineland.com/altavista-eulogy-165366>.

¹⁵⁹ See, e.g., Danny Sullivan, “What Is Google PageRank? A Guide For Searchers & Webmasters,” *Search Engine Land*, April 26, 2007, available at <http://searchengineland.com/what-is-google-pagerank-a-guide-for-searchers-webmasters-11068>.

Yahoo!, AOL, and Ask. Google’s share of queries has not increased since late 2009, remaining at about 66 percent.¹⁶⁰

Figure 5: Shares of U.S. General Search Queries



82. Neither do high shares indicate market dominance in dynamic industries with continual innovation and rapid technological change.¹⁶¹ Although shares are in some instances a useful starting point for determining the existence of monopoly power, and high shares are a *necessary* condition for the existence of monopoly power, they are by no means a *sufficient* condition. In other words, one cannot infer the existence of monopoly power from high shares alone. High shares are not indicative of a lack of competition because they may be a *consequence* of vigorous competition rather than the absence of competition. Monopoly power is the ability to anticompetitively restrict market output and/or anticompetitively exclude competitors for a

¹⁶⁰ comScore. Total Core Searches are used before June 2010, when comScore began reporting Explicit Core Searches; Explicit Core Searches are used from June 2010 to January 2014.

¹⁶¹ The discussion of user shares of general search providers does not accept the premise that the relevant product market is restricted to general search providers, to the exclusion of targeted search firms and other online businesses.

significant period of time without erosion by new entry or expansion of existing competitors. But a high share does not indicate, by itself, the ability to restrict market output and/or anticompetitively exclude competitors. First, existing competitors may have the ability to rapidly increase output (referred to in economics as a high elasticity of supply). An existing competitor with limited scale of users, but with the ability to increase users rapidly, may effectively constrain the pricing and quality decisions of the firm with the large share. What is relevant from an economic perspective is not the starting, or static, market share of the large firm, but the loss of market share to existing rivals that would occur in response to any increase in price or decrease in quality by the large firm. In online services industries, the absence of any significant capacity constraints and low switching costs for users means that rivals can very rapidly expand and take users away if they offer better services. This phenomenon is evidenced by the rapid ascent of new firms and rapid decline of incumbents, as I describe above. Thus, any assessment of market performance must look beyond shares and concentration measures, and assess the capabilities of rivals and new entrants to challenge leading firms.

83. Most online industries are fast-growing and rapidly changing environments, and there is a significant amount of entry and repositioning by various players. Online industries also are characterized by a high degree of competition, both from existing providers as well as new entrants, which drives continuous development and evolution of online services and products. Since many online services are provided for free, online providers compete for users on the basis of innovation and quality, not price. New firms continue to enter, and online platforms with unique services, technologies, and business models continue to competitively challenge each other. It is uncertain what services, technologies, and business models will be successful over the long term.

84. There is no evidence that large online providers have exercised their claimed monopoly power either with regards to advertisers or users. As discussed, there is no reliable evidence that, with respect to advertisers, large online providers set supracompetitive advertising rates. And, it is undeniable that users have received a tremendous amount and variety of valuable online services for free. Despite this zero pricing to users for most online services, some commentators have claimed that users do implicitly “pay” supracompetitive prices. In particular, some claim that because large online platforms face insufficient competitive constraints, they are more likely to collect greater amounts of user data, as well as more sensitive user data, and to violate user

privacy. Senator Al Franken, for instance, has stated that “when companies become so dominant that they can violate their users’ privacy without worrying about market pressure, all that’s left is the incentive to get more and more information about you.”¹⁶² It is claimed that the loss of privacy “is the hidden and undisclosed ‘price’ that consumers pay for many online services.”¹⁶³

85. However, there is no empirical or economic basis for claims that large online platforms are likely to collect more data and more sensitive data from users, or violate user privacy. As discussed, the collection of user data is commonplace by firms of all sizes, and by new entrants and established incumbents. Contrary to claims that large online providers collect more, and more sensitive, user data, smaller firms and new entrants often pose greater risks to user privacy due to their lack of reputation.¹⁶⁴ In fact, large online platforms such as Google and Facebook are often accused of supporting standards for privacy that are too high in order to inhibit competition from smaller rivals.¹⁶⁵

¹⁶² Al Franken, “How Privacy Has Become an Antitrust Issue,” Huffington Post, March 30, 2012, available at <http://www.huffingtonpost.com/al-franken/how-privacy-has-become-an-b-1392580.html>. Similarly, Nathan Newman claims that “you end up with a stunted ‘market’ for valuing user privacy in the search and related sectors, so Google feels less compunction about violating personal privacy to benefit its advertising customers.” (Nathan Newman, “Taking on Google’s Monopoly Means Regulating Its Control of User Data,” Huffington Post, September 24, 2013, available at <http://www.huffingtonpost.com/nathan-newman/taking-on-googles-monopol-b-3980799.html>.) Frank A. Pasquale states that “[d]ominant firms see little to no reason to compete to improve their privacy practices when users are so unlikely to defect. A lemons equilibrium prevails.” (Frank A. Pasquale, “Privacy, Antitrust, and Power,” 20 GEO. MASON L. REV. 1009, 1022 (2013).)

¹⁶³ Scott Cleland, “Why Privacy Is an Antitrust Issue & Why Google is its Poster Child,” Precursor, July 22, 2010, available at <http://precursorblog.com/?q=content/why-privacy-is-antitrust-issue-why-google-its-poster-child>.

¹⁶⁴ For instance, the vast majority of recent FTC enforcement actions on privacy issues identified in press releases during 2013-2014 involved small firms: Goldenshores Technologies, LLC (Flashlight App creator) (<http://www.ftc.gov/news-events/press-releases/2014/04/ftc-approves-final-order-settling-charges-against-flashlight-app>); Fandango, LLC and Credit Karma, Inc. (<http://www.ftc.gov/news-events/press-releases/2014/03/fandango-credit-karma-settle-ftc-charges-they-deceived-consumers>); LabMD, Inc. (<http://www.ftc.gov/news-events/press-releases/2013/08/ftc-files-complaint-against-labmd-failing-protect-consumers>); various data brokers including ConsumerBase, ResponseMakers, Brokers Data, US Data Corporation, Crimcheck.com, 4Nannies, U.S. Information Search, People Search Now, Case Breakers, and USA People Search (<http://www.ftc.gov/news-events/press-releases/2013/05/ftc-warns-data-broker-operations-possible-privacy-violations>); CbrSystems, Inc. (<http://www.ftc.gov/news-events/press-releases/2013/05/ftc-approves-final-order-settling-charges-against-cbr-systems-inc>); Compete, Inc. (<http://www.ftc.gov/news-events/press-releases/2013/02/ftc-approves-final-order-settling-charges-against-compete-inc>); and Path, Inc. (<http://www.ftc.gov/news-events/press-releases/2013/02/path-social-networking-app-settles-ftc-charges-it-deceived>).

¹⁶⁵ See, e.g., Alan Chapell, “‘Do Not Track’: Great For Internet Giants Like Google And Facebook,” AdExchanger, May 29, 2014, available at <http://www.adexchanger.com/data-driven-thinking/track-great-internet-giants-like-google-facebook/>.

86. Large online platforms compete aggressively to develop and implement new privacy tools and protections, and users have more privacy protections than ever before.¹⁶⁶ An important dimension of this privacy-protection competition is information disclosures to users, which includes information on the types of data collected, how the data is stored and used, and whether the data is shared with third parties.¹⁶⁷

87. It is also claimed that large online providers undercompensate users for the value of the data they contribute to online providers—*i.e.*, that users do not receive enough valuable free services in exchange for the value of the data that is collected.¹⁶⁸ For starters, such claims are inconsistent with assertions that large online providers offer superior services to users that smaller rivals cannot match (see discussion, Section III). Such claims also are inconsistent with the irrefutable fact that consumers receive sizable benefits from the free provision of online services.¹⁶⁹

88. Moreover, there may be little or no cost to users of contributing their data. In fact, users often freely contribute personal data. For instance, users freely sign-in to services that collect personal information; write reviews for products, travel destinations, and restaurants; and contribute to social network newsfeeds with information about their personal activities and interests. This suggests that there is not a high cost to users of contributing data and, in fact, users often get utility by contributing such information. And, because online providers require no exclusivity over user data, and multi-homing costs are low, there is no opportunity cost to

¹⁶⁶ For example, Google also has a variety of opt-out options, including incognito browsing that permits private search. While browsing in incognito mode, webpages and downloaded files are not recorded in the user's browsing and download history on Google Chrome, and all new cookies are deleted after closing the incognito browsing window. (Google, "Browse in private (incognito mode)," available at <https://support.google.com/chrome/answer/95464?hl=en>.)

¹⁶⁷ See, *e.g.*, "Google Privacy Policy," which describes "Information we collect", "How we use information we collect", and "Information we share". (Google Privacy Policy, available at <http://www.google.com/policies/privacy/>.) See also, "Yahoo! Privacy Policy," which contains sections titled "Information Collection and Use" and "Information Sharing and Disclosure," among others. (Yahoo! Privacy Policy, available at <http://info.yahoo.com/privacy/us/yahoo/details.html>.)

¹⁶⁸ Nathan Newman, *The Costs of Lost Privacy: Consumer Harm and Rising Economic Inequality in the Age of Google*, 40(2) WILLIAM MITCHELL L. REV. 849, 860-861.

¹⁶⁹ It is claimed that online providers will undercompensate users because users are unaware of the value of their personal data, and how it is being used by online providers (See, *e.g.*, Frank A. Pasquale, *Privacy, Antitrust, and Power*, 20 GEO. MASON L. REV. 1009, 1015 (2013).) However, even if users were unaware of the nature, extent, or value of the data collected by the provider, competition for users nevertheless would compel providers to compensate them for the value of their data through the provision of services. Users need not know the value of their data to be compensated fairly.

contributing data to one provider because users also can contribute the same data to other providers and receive other services for free.

89. Economic theory also does not support claims that dominant online platforms would collect more or more sensitive user data or undercompensate users for the collection of such data.¹⁷⁰ In fact, to the extent that providers with monopoly power collect higher advertising rates than competitive firms, as some have alleged, there would be a greater incentive to attract and retain users. A provider overstepping the collection of user data, or violating user privacy, would risk users, and the loss in revenues would be greater for providers that earn greater advertising revenues per user.¹⁷¹

B. Platform differentiation reduces the propensity to tip to a dominant platform

90. Claims regarding the entrenchment of dominant online platforms assume that more users lead to more user data, better quality, even more users, and to the eventual tipping to a monopoly platform. But these claims are based on the incorrect assumptions that online platforms are homogeneous, and that competition between online platforms for users is largely unidimensional—*i.e.*, that user data is the main driver of service quality and, in turn, quality is the main driver of demand by all users. Under these assumptions, only one platform wins. This may be true for homogeneous platforms in theory, but the assumption of homogeneity is far removed from reality.

¹⁷⁰ The question of whether firms with monopoly power will deviate from the competitive balance between the collection of user data and the provision of high-quality services at low or zero prices is, from an economic perspective, analogous to the issue of whether firms with monopoly power will invest and innovate less than competitive firms. There is an extensive economic literature, both empirical and theoretical, on this issue. The primary conclusion is that the effect of monopoly power on innovation and investment is ambiguous both from theoretical and empirical perspectives. This is because firms with monopoly power may earn greater returns than competitive firms from innovation efforts. Moreover, larger firms may be able to benefit from economies of scale in innovation efforts. (See, *e.g.*, Richard Gilbert, *Looking for Mr. Schumpeter: Where Are We in the Competition-Innovation Debate?*, in 6 INNOVATION POLICY AND THE ECONOMY 159 (Adam B. Jaffe et al. eds., 2006); Wesley M. Cohen & Richard C. Levin, *Chapter 18: Empirical studies of innovation and market structure*, in 2 HANDBOOK OF INDUSTRIAL ORGANIZATION 1059 (R. Schmalensee and R.D. Willig eds., 1989).)

¹⁷¹ The effect depends, however, on whether a firm with monopoly power faces less competition for users. Thus, the net effect depends on the relative competition on the two sides of the market. (See, *e.g.* Benjamin Klein, Andres V. Lerner, Kevin M. Murphy & Lacey L. Plache, *Competition In Two-Sided Markets: The Antitrust Economics Of Payment Card Interchange Fees*, 73 ANTITRUST L.J. 571 (2006), explaining that in two sided markets, the effect of a reduction in competition on prices depends on the *relative* change in the elasticity of demand in each side of the market.) But this indicates that, from a theoretical perspective, the effect of monopoly power on privacy protections is ambiguous.

91. Platform differentiation reduces the risk of “tipping.” This is widely recognized in the economics literature. For instance, Michael Katz and Carl Shapiro write that:

[c]onsumer heterogeneity and product differentiation tend to limit tipping and sustain multiple networks. If the rival systems have distinct features sought by certain customers, two or more systems may be able to survive by catering to consumers who care more about product attributes than network size. Here, market equilibrium with multiple incompatible products reflects the social value of variety.¹⁷²

92. Online platforms are not homogeneous. Far from it—they are highly differentiated in many respects. Online providers compete in a variety of ways to differentiate themselves from rivals and thereby attract potential users. This type of “differentiation competition” is beneficial to users, by giving users more options to find the optimal provider for their needs and preferences.

93. For example, social networking sites offer varied types of services to differentiate themselves.¹⁷³ LinkedIn is a business-oriented social networking service that focuses on professional connections. Twitter is a social networking and microblogging service that focuses on the exchange of quick, frequent messages. LinkedIn and Twitter have grown rapidly, and continue to grow.¹⁷⁴ Other less mature social networking sites also focus on providing users with different types of social media experiences.¹⁷⁵ Tumblr, Pinterest, and Instagram have driven the “visual” web with image- and multimedia-based social networking.¹⁷⁶ Other evolving sites,

¹⁷² See, e.g., Michael L. Katz & Carl Shapiro, *Systems Competition and Network Effects*, 8(2) J. ECON. PERS. 93, 106 (Spring, 1994).

¹⁷³ Social media sites represent a large share of time spent online, with Facebook holding the highest share. In May 2014, social networking sites accounted for 20 percent of total digital time spent, with mobile generating more than 70 percent of the activity. (comScore, “Major Mobile Milestones in May: Apps Now Drive Half of All Time Spent on Digital,” June 25, 2014, available at <http://www.comscore.com/Insights/Blog/Major-Mobile-Milestones-in-May-Apps-Now-Drive-Half-of-All-Time-Spent-on-Digital#imageview/0/>.) About 16 percent of total digital media time spent, including 20 percent on mobile, was spent on Facebook. (comScore, “U.S. Digital Future in Focus 2014,” April 2014, p. 17.)

¹⁷⁴ Twitter and LinkedIn had approximately 62 and 55 million unique visitors as of December 2013 respectively, compared to each having approximately 40 million unique visitors in December 2012. (comScore, “U.S. Digital Future in Focus 2014,” April 2014, p. 16; comScore, “U.S. Digital Future in Focus 2013,” February 2013, p. 14.)

¹⁷⁵ comScore, “U.S. Digital Future in Focus 2013,” February 2013, p. 14; Eli Goodman, “Social Media Monetization in a Mobile First World,” comScore, March 17, 2014, available at https://www.comscore.com/Insights/Blog/Social_Media_Monetization_in_a_Mobile_First_World.

¹⁷⁶ Tumblr reached 43.7 million unique visitors in December 2013, up 42 percent from December 2012, while Pinterest increased unique visitors by 75 percent year-over-year to 50.5 million visitors and Instagram increased

including Instagram, Vine, and Snapchat, focus on social media interaction through content captured on mobile device cameras.¹⁷⁷ Each of these new entrant providers has captured large audiences in a short period of time, driving the overall growth of social networking, while competing by offering differentiated services to their users.¹⁷⁸ The fact that these online providers offer differentiated products does not mean that they do not compete with each other—rather, differentiation is a primary dimension of competition.

94. Another important form of product differentiation is specializing in providing search services focused on specific areas of user activity. Targeted search providers (sometimes referred to as “vertical” search providers) focus on tasks such as shopping (Amazon), travel (TripAdvisor), and local recommendations (Yelp). Even within a particular search category, online providers offer differentiated services and products. In online shopping, for instance, some providers are merchants that fulfill purchase orders directly, such as Walmart or TigerDirect. Other shopping sites such as Nextag and The Find operate as comparison services, allowing users to compare products and prices from many merchants. Online providers of travel services range from “metasearch” sites like Kayak (which cull offers and itineraries from multiple other travel sites), to “travel agent” sites like Expedia (which provide both planning and booking services), to the sites of airline and hotels, to travel search pages within general search engines (*e.g.*, Yahoo! Travel).

95. As discussed above, the relatively short history of the Internet is filled with examples of “dominant” platforms or providers that subsequently were displaced by new firms. Platform differentiation has played a key role in this “creative destruction” by allowing online providers to compete vigorously to meet the needs and demands of users. It cannot be assumed that the most significant competitor, or competitive threat, comes from the rival that is most similar.

unique visitors 125 percent year-over-year to 61.5 million unique visitors in December 2013. (comScore, “U.S. Digital Future in Focus 2014,” April 2014, p. 16; comScore, “U.S. Digital Future in Focus 2013,” February 2013, p. 14.)

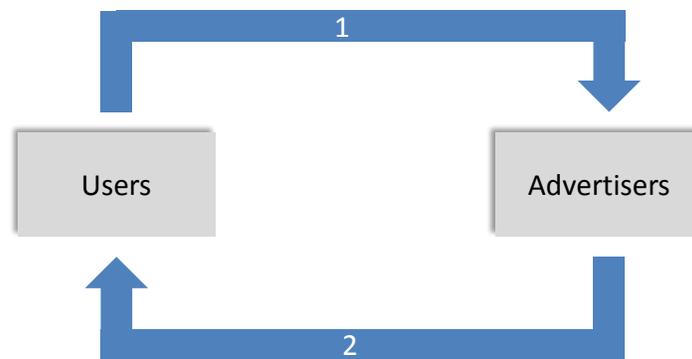
¹⁷⁷ Eli Goodman, “Social Media Monetization in a Mobile First World,” comScore, March 17, 2014, available at https://www.comscore.com/Insights/Blog/Social_Media_Monetization_in_a_Mobile_First_World.

¹⁷⁸ As of January 2014, Instagram had 70 million unique visitors, Vine had 25 million, and Snapchat had 21 million. (Eli Goodman, “Social Media Monetization in a Mobile First World,” comScore, March 17, 2014, available at https://www.comscore.com/Insights/Blog/Social_Media_Monetization_in_a_Mobile_First_World.)

C. Multi-sided network effects do not reinforce tipping to a dominant platform

96. It is claimed that the entrenchment of dominant platforms due to the collection of user data is reinforced by the existence of network effects between users and advertisers.¹⁷⁹ In particular, it is often claimed that a greater number of users makes a platform more attractive to advertisers (step 1 in Figure 6 below), and that a greater number of advertisers enhances user demand for the platform because a search platform with greater advertiser scale can offer more and better-targeted ads to users (step 2).

Figure 6: Claimed User-Advertiser Cross-Platform Feedback Loop



97. It is claimed that these cross-platform network effects between users and advertisers, and the resulting entrenchment of dominant platforms, are analogous to the network effects between users and software developers that were central in the *U.S. v. Microsoft* case. For instance, Nathan Newman states that:

In *U.S. v. Microsoft*, the Court emphasized how such network effects reinforce a monopoly, in that case users wanting a software system with lots of companies writing software for it. The comparison here is to advertisers wanting an advertising system with enough users and, crucially, data about those users to better target that advertising in ways that increase the monetary returns from click-throughs of their ads.¹⁸⁰

¹⁷⁹ See, e.g., Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, last revised August 14, 2014, NYU Information Law Institute, p. 3, forthcoming 40(3) YALE J. REG. (2014).

¹⁸⁰ Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, last revised August 14, 2014, NYU Information Law Institute, p. 29, forthcoming 40(3) YALE J. REG. (2014).

98. Because there are various types of network effects, and each type has very distinct effects on competitive dynamics, it is useful to begin with a brief description of the economics of network effects.¹⁸¹ A product or service exhibits network effects when the value of the service to a user rises with the number of other users of that service. *Direct network effects* refer to the economic phenomenon whereby the members of a user group attract additional members of the *same* user group. The classic example is telephone networks—the greater the number of users that can be reached by telephone, the greater the value of the telephone network to users. Similarly, the greater the number of users on a social network, the greater the value of that network to each user. *Cross-platform* network effects refer to effects whereby members of one user group on a network attract members of *another* user group. One example of such multi-sided platforms are payment card networks, which are demanded by two distinct, inter-related groups of consumers—cardholders (who use the cards to make purchases) and merchants (who accept the cards as payment for purchases). All else equal, the greater the number of merchants that accept a payment card, the greater the value to cardholders; and, the greater the number of cardholders that carry the card, the greater the value to merchants.¹⁸²

99. The claim that the multi-sided aspect of online platforms inherently leads to “tipping” and entrenchment to a dominant platform is based on an incorrect assumption regarding multi-sided platforms. The fact that a platform is multi-sided does not mean that there are significant cross-platform network effects. In fact, cross-platform network effects for most online businesses appear to be quite limited. And, the existence of cross-platform network effects does not imply that an industry is likely to tip to a dominant provider. In many markets characterized by cross-platform network effects, multiple platforms can and do exist and compete fiercely.¹⁸³ For instance, multiple credit card networks (*e.g.*, Visa, MasterCard, American Express, Discover, and various debit networks) have competed and garnered substantial market shares for many

¹⁸¹ For a comprehensive discussion of network effect, see Michael Katz & Carl Shapiro, *Systems Competition and Network Effects*, 8 J. ECON. PERSP. 93 (1994); S. J. Liebowitz & Stephen E. Margolis, *Network Externalities: An Uncommon Tragedy*, 8 J. ECON. PERSP. 133 (1994); Stan J. Liebowitz & Stephen E. Margolis, *Network Effects*, THE NEW PALGRAVE DICTIONARY OF ECONOMICS AND THE LAW 673 (Peter Newman ed., 1998).

¹⁸² See, *e.g.*, Benjamin Klein, Andres V. Lerner, Kevin M. Murphy & Lacey L. Plache, *Competition In Two-Sided Markets: The Antitrust Economics Of Payment Card Interchange Fees*, 73 ANTITRUST L.J. 571 (2006).

¹⁸³ Michael Katz & Carl Shapiro, *Systems Competition and Network Effects*, 8 J. ECON. PERS. 93, 106 (1994).

years, and the market has not “tipped.” Other examples of vigorous competition between multiple networks include video game consoles and smartphones.

1. Multi-sided network effects for advertisers are limited

100. I first address the claim that if a rival provider had more users, then it would provide greater value to advertisers and, thus, would be able to attract more advertisers. From an advertiser’s perspective, the value of an online platform is that it allows the advertiser to reach users. Thus, all else equal, advertisers want to be where users are. However, the competitive implications of cross-platform network effects are fundamentally altered by the fact that most online providers price on a per-click or per-impression basis. For instance, Google and Bing generally price their search advertising on a cost-per-click basis, whereby an advertiser pays only when a user clicks on the advertiser’s ad.¹⁸⁴ Thus, the amount that an advertiser pays per click or per ad impression generally is not affected by its total advertising expenditures. One implication of this pricing structure is that, while an advertiser may derive more value in advertising on a platform with more users because the advertiser’s ads may obtain more user clicks or views, advertising on such a platform entails proportionately higher costs. Thus, in theory, it is not necessarily preferable for a firm to advertise on a larger platform versus a smaller one. The cost to the advertiser per user click or per user view may be higher or lower on a large platform compared to a smaller platform.¹⁸⁵

101. This economic effect of per-click or per-impression pricing is reinforced by the fact that there are, at most, small fixed costs associated with advertising on a particular platform. There appear to be little or no fixed, platform-specific investment by advertisers, such as set-up costs or lump-sum payments.

¹⁸⁴ See, e.g., Google AdWords Help, “How costs are calculated in AdWords,” available at <http://support.google.com/adwords/bin/answer.py?hl=en&answer=1704424>.

¹⁸⁵ See, e.g., Mark Armstrong, *Competition in 2-Sided Markets*, 37 RAND J. ECON 668, 669 (2006): “cross-group externalities are weaker with per-transaction charges, since a fraction of the benefit of interacting with an extra agent on the other side is eroded by the extra payment incurred. If an agent has to pay a platform only in the event of a successful interaction, then that agent does not need to worry about how well that platform will do in its dealings with the other side. That is to say, to attract one side of the market, it is not so important that the platform first gets the other side ‘on board.’” See also, Geoffrey A. Manne & Joshua D. Wright, *Google and the Limits of Antitrust: The Case Against the Antitrust Case Against Google*, 34 HARVARD L. & PUB. POL. 171 (2011).

102. The presence of *congestion* further reinforces advertisers' incentives to patronize smaller online platforms rather than a large one. In some markets, the presence of additional members of one group on a network makes that network or platform less valuable to members of the same group. This is especially likely in a market with cross-platform network effects, where users on one side of the platform may compete with one another for the attention and patronage of users on the other side of the platform. A heterosexual singles bar provides a good example. All else equal, having more men in a singles bar tends to decrease the attractiveness to men because there is more competition to attract women. Similar effects can be expected to arise in the case of an online advertising platform. From an advertiser's perspective, having a greater number of rivals advertising on a given web site may make that site a less desirable place to advertise. This is so because the advertiser has to compete for users' attention. In addition to the congestion effects due to rivalry between advertisers offering substitute products, there are limited spaces available for online ads. Bidding competition between advertisers for scarce slots raises the cost of advertising, creating incentives to utilize alternative advertising platforms. Because of congestion, some advertisers may prefer a small platform with fewer users and fewer advertisers to compete with, rather than a larger platform with more users and more advertisers. While advertisers want to be where users are, advertisers do not want to be where their rivals are.

103. Per-click and per-impression pricing, low fixed costs of advertising on a given platform, and congestion increase incentives for advertisers to multi-home. Because of per-click and per-impression pricing, an advertiser pays the same amount per user click or per ad impression whether the advertiser divides its campaign across multiple platforms or advertises in only one. And, advertising in online platforms generally does not involve platform-specific set-up costs, lump-sum payments, or other fixed costs that the advertiser has to incur. Multi-homing costs also are reduced by the fact that the costs of exporting data between different online platforms are very low.¹⁸⁶ Rival platforms, as well as third-parties, reduce the costs of porting by, for

¹⁸⁶ For instance, Microsoft advertised the ability to "Easily import your Google ad campaigns." (Microsoft Advertising adCenter, available at http://advertising.microsoft.com/small-business/yahoo?s_cid=us_ya_US2763.) A post on the adCenter Desktop Team Blog by an AdCenter manager describes the porting process as a simple three-step procedure: "1. Simply export your account using Google's AdWords Editor Application. Click File, click Export Spreadsheet (CSV), then select Whole Account. 2. In adCenter Desktop, click the import button on the Ribbon menu and select the Google option. This wizard will guide you through the steps of selecting your Google file and quickly reviewing the mapping between Google's and adCenter's columns. 3. Once your file is imported, the last step allows you to review basic statistics on what was imported." (Abid Kadir, "Importing your Google ad campaigns into adCenter," adCenter Desktop Team Blog, July 22, 2010, available at

example, offering compatible interfaces, tools that make it easy to import an advertising campaign, and per-click pricing.¹⁸⁷

104. Multi-homing can have important competitive implications. In particular, multi-homing weakens the feedback cycle and diminishes the competitive significance of cross-platform network effects. User multi-homing allows various networks, including networks with small scale, to compete effectively, and diminishes the propensity of a market to tip to a dominant platform.

2. *Multi-sided network effects for users are weak or nonexistent*

105. The second part of the user-advertiser feedback loop is the claim that a greater number of advertisers enhances user demand for the platform. However, it is highly unlikely that users' demand for a platform is substantially driven by the availability of advertisements. Cross-platform network effects on the user side of the market appear to be weak, at best. Although some users may desire to be exposed to advertising, many other users ignore paid results and/or prefer to be on a site with less advertising.¹⁸⁸ In the context of search, one reason is that organic search results are often superior to sponsored results from the users' perspective. In fact, some users may place negative values on having too many advertisements. These negative values that users place on advertisers are an example of a phenomenon called *repulsion*, whereby platform participation by members of one group (*e.g.*, advertisers) may repel members of another group

<http://blogs.msdn.com/b/adcenterdesktop/archive/2010/07/22/importing-your-google-ad-campaigns-into-adcenter.aspx>.) Other websites advise advertisers to use Google editing tools to create their online campaigns even if they intend to run these campaigns solely on competitors' online search platforms. (See, *e.g.*, David Szetela, "Google AdWords Editor a Great Tool for Content – and for Yahoo/Microsoft!", Search Engine Watch, May 11, 2008, available at <http://searchenginewatch.com/3629448>.)

¹⁸⁷ For instance, Microsoft launched version 8.1 of its adCenter Desktop, which includes an Import Campaign feature, which allows advertisers automatically to port campaign data directly from Google AdWords to Microsoft adCenter. (Brian Utter, "Introducing adCenter's Import Campaigns feature: Bringing Added Choice and Flexibility to A Desktop Near You," Bing Ads Blog, November 2, 2011 available at <http://community.microsoftadvertising.com/blogs/advertiser/archive/2011/11/02/introducing-adcenter-s-import-campaigns-feature-bringing-added-choice-and-flexibility-to-a-desktop-near-you.aspx>.)

¹⁸⁸ An eye-tracking study conducted by User Centric, a research firm, compared the amount and distribution of user attention paid to different types of results on Bing and Google search-results pages. The study found that users spend considerably more time looking at organic results than paid results. Users spent an average of 14.7 seconds viewing organic search results on Google, while spending 2.8 seconds and 4.4 seconds on average viewing Google's top and right-hand side sponsored results, respectively. (User Centric, "Eye Tracking Bing vs. Google: A Second Look," January 27, 2011, available at <http://www.usercentric.com/news/2011/01/26/eye-tracking-bing-vs-google-second-look>.)

(e.g., users). Advertiser-supported media can exhibit this pattern of repulsion and attraction. Readers or viewers may want to avoid the advertisers, while advertisers want to be where the readers or viewers are.

106. Given the weakness of users' demand for advertisers, it is highly unlikely that multi-sided network effects have a material effect on competition between online platforms. If a smaller rival or new entrant offers a better service, network effects do not prevent users from switching. And, once users switch, advertisers likely would follow. Thus, there is no user-advertiser feedback loop that locks in users to a dominant platform. This makes the multi-sided network effects for advertiser-funded online business distinct from the network effects at issue in the *Microsoft* case.¹⁸⁹

107. Even if there were multi-sided network effects between users and advertisers, the competitive impact would be limited by various factors. For instance, multi-homing and easy switching facilitate entry and make the coexistence of multiple competitors more likely.¹⁹⁰ As discussed, users face little, if any, costs of switching and multi-homing. And, not surprisingly, users often make use of multiple platforms.¹⁹¹ User multi-homing makes it possible for advertisers to reach a given user on multiple platforms.

108. The discussion in this section pertains to cross-platform network effects between users and advertisers, and does not intend to argue that there are no network effects in any online businesses. In some online platforms, such as social networks (e.g., Facebook) or review sites (e.g., Yelp!), there may be important *direct*, or *single-sided* network effects, in which the value of the platform to users increases with a greater number of users. However, even if there are important direct network effects, there also may be important platform differentiation between providers that allows smaller rivals to be successful. Moreover, in the context of these platforms, low switching and multi-homing costs also may limit the scope of direct network effects.

¹⁸⁹ In fact, Nathan Newman recognizes that “Google’s search users don’t need advertisers, but advertisers need users.” He also states that “[w]hile some users find some search advertising useful, it is not an essential feature from a user perspective and even objectionable to many...” (Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, last revised August 14, 2014, NYU Information Law Institute, p. 8, forthcoming 40(3) YALE J. REG. (2014).) However, he fails to recognize the implication of this for his claims that network effects lead to entrenchment of a dominant platform.

¹⁹⁰ See, e.g., Aaron S. Edlin & Robert G. Harris, *The Role of Switching Costs in Antitrust Analysis: A Comparison of Microsoft and Google*, 15 YALE J. L. TECH. 169 (2013).

¹⁹¹ See discussion, Section III.A.1.

V. Conclusions

109. Given the lack of real-world evidence of market dominance, anticompetitive effects, or harm to competition and consumers resulting from the collection of user data, there is no sound basis for more aggressive antitrust intervention in online markets, or for greater antitrust scrutiny of the data collection practices of large online platforms. Such intervention would hamper competition and chill innovation that currently provides immense benefits to consumers of online services.

110. This paper focuses on claims regarding market dominance of online platforms supposedly achieved through the collection of user data. As I have discussed, assumptions that the collection of user data leads to large economies of scale, and to the entrenchment of dominant platforms in online markets are unsupported by empirical evidence. However, even if there were significant economies of scale from the collection of user data in online markets, the mere existence of such scale economies do not establish that large providers have monopoly power or that there is harm to consumers and competition, and do not justify more aggressive antitrust intervention. And, even if (*arguendo*), some online platforms were found to possess monopoly power, such a finding also would not support calls for antitrust intervention in such markets to the extent that platforms achieved that monopoly power through legitimate, competitive means.¹⁹²

111. A critical question for competition analysis and policy is whether a firm has engaged in anticompetitive conduct that deprives rivals of scale to an extent that inhibits their ability to compete and, therefore, undermines the ability of rivals to competitively constrain the conduct of the firm in question. Another critical question is whether there are procompetitive justifications for a particular practice, since legitimate business conduct (such as lower prices or innovation) can harm competitors but benefit competition and consumers. But proponents of greater scrutiny of data collection by large online providers fail to provide any concrete theories or empirical evidence regarding widespread conduct related to the collection of user data that reasonably could be construed as anticompetitive. Some critics suggest that the collection of user data is

¹⁹² The courts have recognized that the possession of monopoly power is not an antitrust offense. For instance, in *Trinko*, the Supreme Court noted that monopoly profits are what “attracts ‘business acumen’ in the first place; it induces risk taking that produces innovation and economic growth.” (*Verizon Commc'ns Inc. v. Law Offices of Curtis V. Trinko, LLP*, 540 U.S. 398, 407 (2004).)

itself anticompetitive conduct when it constitutes an invasion of user privacy.¹⁹³ However, theories that violating user privacy amounts to anticompetitive conduct, by somehow depriving rivals of user data and thereby inhibiting their ability to compete effectively, are far-fetched, at best.

112. Despite the lack any reasonable theories regarding general anticompetitive conduct by large online providers, a number of “remedies” have been proposed, including restrictions on the collection of user data, mandating that users be able to easily port data to rival providers, mandating opt-in consent for user data collection, and restrictions on expanding into or acquiring vertically-related businesses. For starters, these proposed remedies are inapposite because they are not tied to any specific allegations of anticompetitive conduct by online providers. General restrictions on data collection efforts of online providers would hurt small providers and new entrants more than large incumbents, as they would increase barriers to entry and expansion and harm competition, as the FTC and others have noted.¹⁹⁴ Restrictions on data collection efforts that applied only to large online providers would inefficiently act as a success tax, penalizing firms that are successful because they offer high-quality services that users demand, and would distort market outcomes and inhibit innovation. Such restrictions would harm consumers by inhibiting online providers’ ability and incentive to provide high-quality services at low or zero cost. As the FTC concluded, “regulating the privacy requirements of just one company could itself pose a serious detriment to competition in this vast and rapidly evolving industry.”¹⁹⁵ While restrictions on the data collection practices of large online providers may help smaller rivals, protecting rivals is not equivalent to promoting competition and benefiting consumers.

¹⁹³ See, e.g., Nathan Newman, “Search, Antitrust and the Economics of the Control of User Data,” working paper, last revised August 14, 2014, NYU Information Law Institute, p. 36, forthcoming 40(3) YALE J. REG. (2014).

¹⁹⁴ Remarks of Commissioner Maureen K. Ohlhausen, Digital Advertising Alliance Summit, Washington, D.C., June 5, 2013, p. 6, available at <http://www.ftc.gov/public-statements/2013/06/remarks-commissioner-maureen-k-ohlhausen>: “new restrictions on the ability of companies to collect or disseminate information could erect barriers to entry in what has historically been a very open sector of the information economy. Instituting new privacy restrictions may preclude new entrants from obtaining valuable consumer information that incumbent competitors already possess.” See also, James Campbell, Avi Goldfarb, & Catherine Tucker, “Privacy Regulation and Market Structure,” working paper, December 9, 2011: “though privacy regulation imposes costs on all firms, it is small firms and new firms that are most adversely affected”; Catherine Tucker & Avi Goldfarb, “Is privacy an antitrust problem?”, Digitopoly, April 2, 2012, available at <http://www.digitopoly.org/2012/04/02/is-privacy-an-antitrust-problem/>.

¹⁹⁵ Statement of Federal Trade Commission Concerning Google/DoubleClick, FTC File No. 071-0170, December 20, 2007, p. 2, available at http://www.ftc.gov/system/files/documents/public_statements/418081/071220googledc-commstmt.pdf.