

CARMELO GENNAMO

VALUE PRESERVING PLATFORM REGULATION

NETWORK EFFECTS, PLATFORM VALUE AND REGULATORY REMEDIES



DIGITAL MARKETS COMPETITION FORUM
www.cbs.dk/dmcf

1ST (ONLINE) WORKSHOP – 16 JULY 2020
SUMMARY REPORT

ABOUT THE DIGITAL MARKETS COMPETITION FORUM

The DMC Forum is an initiative to bridge academic research and practice to discuss the different perspectives on the ways digital platforms create value in the digital economy and the pressing challenges for competition regulation in digital markets. Led by Carmelo Cennamo, Strategy professor at the Copenhagen Business School, the mission of the DMC Forum is to foster a progressive debate on the role of digital platforms in the economy and the new competitive forces in digital markets, and their implications for the regulatory framework.

ABOUT THE REPORT'S AUTHOR

Carmelo Cennamo is MSO Professor of Strategy at Copenhagen Business School, and the Founding Director of The Digital Markets Competition Forum. He is also an Affiliate Professor at SDA Bocconi School of Management. His research focuses on competition in digital platform markets, and on business ecosystems. His ongoing projects concern the role of market design and ecosystem orchestration by platform firms and the implications for digital transformation of sectors and competition policy.

DISCLAIMER

The DMC Forum event for which this report has been prepared has received the support of Facebook. This report is the outcome of academic independence. It offers an account of the views expressed by the panelists, and contextualizes them within the existing related (management) research. The opinions offered herein are purely those of the author(s) in a personal capacity and are not attributable to any institution with which they are associated. The views expressed in this report do not necessarily correspond to those of Facebook, Copenhagen Business School, or to any participant or sponsor of the DMC Forum.

ABOUT THE FORUM'S PANELISTS

Andrei Hagiu is Associate Professor of Information Systems at the Boston University, and Associate Director for the platform's initiative; digital sector. A leading expert on platform strategy and business models, his research focuses on the defining attributes of multisided platforms, coordination strategies, and data-driven competitive advantage.

Tobias Kretschmer is Professor of Management at the Ludwig-Maximilians-Universität München (LMU), and Head of the Institute for Strategy, Technology and Organization. His research covers different areas, including competitive strategy, network industries, organization design, and applied industrial organization.

Melissa Schilling is the Herzog Family Professor of Management at New York University, Stern School of Business, and the Director of Technology & Innovation Area of Fubon Center. Author of the bestseller textbook; Strategic Management of Technological Innovation, her research focuses on innovation and strategy in high technology industries, with an interest in platform dynamics, networks, creativity, and breakthrough innovation.

Marshall van Alstyne is Professor of Information Systems at the Boston University. A leading expert in network business models and "two-sided networks", and coauthor of "Platform Revolution", he conducts research on information economics, covering such topics as communications markets, the economics of networks, intellectual property, social effects of technology, and productivity effects of information. His co-authored article on platforms and two-sided networks is a Harvard Business Review top 50 of all time.

THIS REPORT IS PUBLISHED BY:
DEPARTMENT OF STRATEGY AND INNOVATION

NOVEMBER 2020

FRONT PAGE PHOTO:
JESS BAILEY –UNSPASH

Table of Contents

1. Introduction	1
2. (When) Is Network Size Anti-Competitive?	3
2.1 Network Size and Entry Barriers: The Limits of Scale	3
2.1.1 Network Saturation	3
2.1.2 Diminishing Returns and Local Bias	4
2.1.3 Within-period and Inter-temporal Network Effects	5
2.1.4 Switching Costs, Porting and Multihoming	5
2.2 Network Size: Policy Considerations	6
3. Data Size: When do Data lead to Network Effects?	9
3.1 Conditions for Data Network Effects	9
3.2 Exponential Growth vs. Thresholds in Data Scale	11
3.3 Data Network Effects: Policy Considerations	11
3.3.1 Self-preferencing	12
3.3.2 Data sharing	13
3.3.3 Mandating Transparency	14
References	15

1. Introduction

The digitization of the economy is transforming not just the internal firms' operational processes but entire sectors by redefining how firms create and deliver value. This is achieved through new ways of organizing firms' value chains and interfirm relationships, which now increasingly occur not in isolation but in digital ecosystems and digital marketplaces. Digital platforms represent the engine of this transformation: they enable new structures of economic relationships, facilitate and manage interactions among multiple groups of users, and create new roles and innovation opportunities by empowering value-adding contributions by external firms and users.

Digital markets are not just another market channel; they represent a paradigm shift in the way companies generate and deliver value to final customers, and thus the way they compete. Digital platforms are the ones that enable the emergence of digital markets and guarantee their functioning by setting the rules for participation and by coordinating participants' interactions. While this market orchestration power has produced large benefits for consumers and the economy at large, those benefits may hide risks associated with market power concentration.

There is increasing and pressing demand on policy makers to contrast the market power of platforms; the concern being that platforms can leverage their size and the network effects to exert a market gatekeeping stronghold that can ultimately harm competition or users indeed.

The Digital Markets Competition Forum was set up with the specific mission of bridging academic research and practice to discuss the different perspectives on the ways digital platforms create value in the digital economy and the pressing challenges for competition regulation in digital markets. In July 2020, the first DMC Forum event took place, hosting a panel of academic experts¹, debating and interacting with other experts in the audience on these issues. Panelists' views and the ensuing debate during the DMC Forum centred on some specific themes, namely:

- the distinction between size and network effects; and between network effects and data-based network effects.
- the role that network effects play for barriers to entry.
- whether network effects taking place in platforms are of similar nature to those of traditional technological standards and utilities.

The current regulatory debate on digital markets and the need to regulate digital platforms is anchored in two fundamental beliefs: successful platforms are often protected from rivals' entry by network effects in both users and data; platforms can leverage these network effects to expand their services (and network) to adjacent markets in a way that further blocks new entrants. The concern is that, as a result, platforms may develop business models and a market gatekeeping stronghold that are harmful or unfair to business and individual users.

One emerging logic for regulatory intervention treats platforms as the "new utilities" of the digital economy – i.e., digital infrastructures that need to guarantee equal access to and use of data and network resources. As per the case with traditional utilities such as energy or telco, this logic calls for

¹ The panel included: prof. Melissa Schilling (NYU), prof. Andrei Hagiu (BU); prof. Tobias Kretschmer (LMU); prof. Marshall Van Alstyne (BU), and prof. Carmelo Cennamo (CBS, and panel chair). This report summarizes the panelists' views and related discussion by contextualizing the discussion in the related management literature on these aspects.

a separation between the network infrastructure and the services that run through it, with proposed remedies ranging from imposing interoperability on the core service to mandating data access and data sharing. This, the argument goes, would guarantee equal access to services and curb platform market power by imposing remedies such as compatibility and interoperability of services across networks.

This view is somewhat in contrast with much of the research in the management literature, which conceives of digital platforms, and their connected ecosystems, as new modes of organizing economic activity and creating greater value for the consumer. Digital platforms are viewed as complex technology systems and ecosystems, which involve specific (rather than generic) complementarities and an active governance to steer the technology evolution and drive innovation and value creation. Unlike the traditional sectors where firms make choices within a given market and sector context, platform firms can be seen as architects of choice, in that, by building ecosystems they create and shape new structures of economic relationships in which value can take place. In addition, they govern the interactions among different actors to curate a menu of value options that the customer is free to choose from. In this sense, the network and digital technology infrastructure are not neutral to consumer choices; this curation or governance activity is central to the value creation process.

This report explores the implications of these views by revisiting first the role of network size for network effects, then discusses when data can lead to network effects dynamics and create entry barriers or when they might stimulate greater innovation and competition. Finally, it offers some reflections on how useful is viewing digital platforms as the new utilities of the digital economy; and concludes with a brief account of the challenges and issues with the writing of effective competition law.

2. (When) Is Network Size Anti-Competitive?

Economic activities in the digital economy take place largely in multisided markets, which emerge around and are organized by digital platforms facilitating value-creation exchanges between different groups of users (Evans, 2003; Parker and Van Alstyne, 2005; Hagiu, 2005; Rochet and Tirole, 2006). Because participation of one group to the platform network increases the value for groups on the other side of the platform to participate, increasing returns to scale from participation of users on the different sides, or indirect network effects, arise and can lead to the “winner-take-all” dynamics (Eisenmann, Parker & Van Alstyne, 2006). Thus, multisided markets are prone to a concentrated or monopolist structure.

While monopolistic positions might well be the outcome of platform competition in the quest of generating greater value for users, the concern, from a competition regulatory perspective, is that large platforms can leverage size of their user network to reinforce their dominant position and curtail competition. Foreseen remedies that have been proposed to contrast these effects are wide-ranging and can go from restrictions for large platforms to expand into other markets, or participate as good/service provider on the platform marketplace they control, to breaking up “Big Tech” companies and designate tech platforms as “platform utilities”².

The presumption is that indirect network effects become stronger the bigger the platform becomes, in an exponential fashion, such that winner-take-all (WTA) is an inevitable course. However, recent research shows that those dynamics are much more intricate, questioning to some degree the winner-take-all logic (see e.g. the analysis by Lee et al. 2006). There are a number of factors that put a break on the increasing returns process of network effects, which implies that value does not always grow with a larger network, certainly not exponentially so, and that platforms with smaller networks can and do often compete successfully with larger platforms. We briefly discuss these factors before discussing the implications for policy competition.

2.1 Network Size and Entry Barriers: The Limits of Scale

2.1.1 Network Saturation

A first factor to consider when assessing the anti-competitive effects of network size is “**network saturation**”³ – the point at which the size of the network is enough to foster reinforcing complementarities and engender positive spillovers; past that threshold, there is little to be gained in terms of additional user benefits (e.g., Boudreau and Jeppesen, 2015; Cennamo 2018). A low network saturation threshold implies that there will be enough opportunities for customizing the network through differentiated features to cater to the specific needs of subgroups of users and create specialized networks. This implies that, in principle, greater market entry and platform competition through differentiation can occur (Eisenmann et al. 2006; Halaburda, Piskorski and Yildirim 2017).

² Famously, breaking up Amazon, Facebook and Google is a political manifesto advanced by Senator Elizabeth Warren: <https://medium.com/@teamwarren/heres-how-we-can-break-up-big-tech-9ad9e0da324c>

³ The concept has been put forth by Melissa Schilling during her presentation in the online workshop on “...” held by the Digital Markets Competition Forum, July 17th, 2020.

In the context of early movers and followers competing for dominance in the next-generation platform technology (in the US home video game market) Cennamo (2018) shows that early movers reaching quick network saturation induced switching of complement providers to smaller, but growing platform networks (see also Schilling 2002). Similarly, Venkatraman and Lee (2004) shows that complement providers will more likely launch their “best,” most novel products in smaller platforms, which offer a less crowded, more visible and possibly more profitable environment for their products compared to the large dominant platform. Similar effects have also been shown in the context of user-generated innovation (Boudreau and Jeppesen 2015).

2.1.2 Diminishing Returns and Local Bias

Research also shows that network effects can be diminishing at certain point, that is, they exhibit **diminishing returns to scale** under some conditions (see e.g., Casadesus and Halaburda 2014; Cennamo 2018; Lee et al. 2006; Panico and Cennamo 2020).

Panico and Cennamo (2020) model indirect network effects as a function of end users’ preferences for innovativeness (quality and novelty of platform complements) and size (network size/number of complements) of the ecosystem. They show that, depending on the composition of the type of platform users at a given time, the intensity of indirect network effects can vary: more can be less, and less can be more. For instance, when users value innovativeness relatively more, indirect network effects will be strong at early stages of the platform market and will then be weakening as the platform size increases.

Similarly, Casadesus and Halaburda (2014) show that the platform can create more value for users by limiting the number of applications available. This is the case when, even in the presence of indirect network effects, applications also exhibit *direct* network effects – that is, users are better off using the same applications as other users due to increased consumption benefits from interacting and exchanging with other users (e.g., users playing the same massively multiplayer online game or using the same videoconference application). In such cases, users will face a coordination problem over the application of choice to converge on and a “commons” problem may arise; that is, users may tend to consume more applications than the number that would maximize joint utility. In such cases, the platform needs to coordinate the demand and supply side of the platform market by restricting the size of the network rather than maximizing it.

In the context of online dating platforms, Halaburda and Oberholzer-Gee (2014) and Halaburda, Piskorski and Yildirim (2017) show that, due to asymmetries in user preferences and “attraction” across sides, a lower, but more homogenous set of users for potential matches, can be preferable to a large enough set of users. This explains why eHarmony, with a much smaller network, can successfully compete with the dominant platform Match.com in the online dating market on the basis of a differentiated approach predicated on a more “curated” membership and selective matching service.

Several platform contexts might be subject to diminishing returns in fact, particularly when users have a preference to interact with a specific, narrow set of users, a tendency that is referred to as “**local bias**” (Lee et al. 2006), and that can be widely present in social networks among some groups of users (see e.g., Morlok et al. 2018).

2.1.3 Within-period and Inter-temporal Network Effects

Another factor to consider when assessing the reinforcing or diminishing nature of network effects is the distinction between **within-period** (or, **one-time**) vs. **inter-temporal network effects** (Zhou, Zhang and Van Alstyne 2020). Zhou et al. (2020) show that, even in the presence of strong network effects, a large network of users, per se, does not necessarily create entry barriers. The reason is that, **in most cases, strong network effects are short-lived**; there is strong attraction across user groups in one period, but this intensity of network effects does not last over time. That is, *intertemporally*, there are diminishing to weak or null network effects. Said differently, network effects have a strong decay effect – while the number of active users in one-period on one side exerts a strong attraction for (active) users on the other side, the total number of (registered) users on the network will have but very limited value for users on the other side to engage. There is thus an important difference between active and passive users, “new” vs. “old” users, and “flow” vs. “stock”. Uber is a case in point. The strength of network effects is not constant over time and might quickly diminish with waiting time. In ongoing analysis, Zhou et al. (2020)⁴ find that, after 5 minutes, consumers seem to be empirically indifferent between using Uber or alternative services. A similar effect might be in place for social networks and media platforms: unless new content is constantly offered and interactions are stimulated, users might lose interest in the service.

2.1.4 Switching Costs, Porting and Multihoming

Multihoming is an important factor that can reduce the likelihood that one platform will win the entire market. There is evidence for software platforms that the network size of one platform can create positive spillovers for competing technologies and be pro-competitive when multihoming costs for software providers are low compared to platform-specific innovation costs (Corts and Lederman 2009; Landsman and Stremersch 2011)⁵. By contrast, Lee’s (2013) findings suggest that exclusivity deals can help small platforms to differentiate on the basis of content and compete against large platforms. For smartphones, Bresnahan et al. (2015) find that multihoming would have limited impact on platform competition and market share between Android and iOS, since apps that are more attractive and thus have many users will multihome to both platforms anyhow. This echoes the concept of “competitive bottlenecks” advanced by Armstrong (2006)⁶.

When considering the effects of multihoming on competition (and on consumer welfare in general), one should also assess the hidden costs related to potential losses in innovation and quality performance of multihoming complements. Precisely because multihoming complements can reduce

⁴ More generally, using data from Groupon’s distinct product categories, Zhou et al. (2020) find that, while within-period network effects are strong, intertemporal network effects are rather weak. They also find heterogeneity in network effects across distinct product categories; the inter-temporal effect of customer base is positive for personal-care services such as beauty or fitness, but absent for other categories such as restaurant services. Users may lose interest over time in such products or even disintermediate the platform.

⁵ The core logic is that in an environment where non platform-specific fixed costs (of innovation) are increasing and multihoming costs (“porting costs”) are decreasing, multihoming will increase – software providers find it economically more rewarding to develop for and sell their products on multiple platforms.

⁶ The logic there is that when one side’s group of users (say, consumers) single-home, the other side (content providers) needs to affiliate with the chosen platform of the single-homing side to interact with that group. Thus, platforms represent independent separate markets and be bottlenecks for the multihoming side – they can have monopoly power over providing access to their single-homing customers and thus charge high prices for access to multi-homing customers. However, because they compete fiercely for the single-homing customers, the profits generated from the multihoming side are to large extent passed on to the single-homing side in the form of low or zero prices.

differentiation across platforms, platform owners may invest heavily in technology design to gain an edge (Zhu and Iansiti 2012); platform architecture differences such as differences in the core operating system and interfaces may thus become pronounced (Anderson et al. 2014; Cennamo et al. 2018). These differences, in turn, can impose important design trade-offs on complementors, increase multihoming costs, and manifest in lower quality performance of the multihoming complement on the multihomed platform compared to the platform they were originally designed for, and on platforms with higher platform architecture complexity⁷ compared to those whose core technology is easier to design for (Cennamo, Ozalp and Stremersch 2018). **Platform complexity** can be an important strategic dimension indeed, influencing the extent new entrants can disrupt the ecosystem of incumbent platforms and induce user switching (see analysis by Ozalp, Cennamo and Gawer 2018).

In sum, network size does not produce mechanically anticompetitive effects; it can create positive spillovers for competing technologies and be pro-competitive when multihoming costs are low compared to innovation costs. Multihoming's benefits should be weighed against costs of potential innovation losses and degraded quality performance of complements.

2.2 Network Size: Policy Considerations

The bottom line for competition and market contestability considerations is that **a large network of users, per se, does not necessarily preclude entry or effective competition from other platforms**. This might be due to diminishing returns or local bias, weak intertemporal network effects or low multihoming costs. Network effects are far more complex than the mainstream debate seems to assume

Because platforms constantly innovate in terms of functionalities and applications that let users engage more intensively, they might, *de facto*, be creating the type of user clustering environments in their networks that can promote **“local bias” and diminishing returns**, making the overall market more contestable rather than winner-take-all context. This implies that network size might be the wrong metric to focus on. Platforms with small network but that nurture stronger complementarities among their users can and do often compete successfully with larger platforms – Apple iOS is a case in point.

Another key consideration for competition policy is the need for understanding the factors that reinforce or weaken **intertemporal network effects**. Needed is a simple framework to clearly distinguish the level of participation and activity on the platform that is due to inertial effects from the existing network and what part is due to platform orchestration activity and innovations in its core technology and services. We lack empirical evidence in this realm; but this kind of analysis is needed to develop new tools for testing and teasing out these effects.

⁷ Cennamo et al. (2018: 464) refer to platform complexity as “the number of interdependent components of the platform’s core technology interacting with the platform’s complements through specialized interfaces.” This rests on the idea that the larger the number of unique components interacting with a complement, and the higher the interdependence between system components that cannot be easily abstracted by standardized interfaces, the more complex the system.

When considering the effects of **switching costs and multihoming**, a broader analysis that accounts also for technology-related multihoming costs is warranted. Market regulatory authorities should focus on, case-by-case, the possible artifices that can increase porting costs or block porting to competing platforms ‘tout court’ to assess the anticompetitive implications of those specific practices rather than assuming that a large network size in itself limits multihoming. However, losses in terms of technological innovation and degraded quality of multihoming complements due to the hidden (technology-related) costs of multihoming should be weighed against the possible gains in competition. There is a risk, in fact, that both competition and innovation might be hindered when platform technological differences matter - complementors might default on the platform that is easier to develop for, with possible market tipping effects and potential losses in platform’s technology innovation.

One pressing concern, from a competition regulatory perspective, with large network size is that large platforms can leverage their dominant market position and user network size to expand their services into adjacent markets; a practice known as **platform envelopment**⁸ (Eisenmann et al. 2011). By combining its own functionality with that of the target in a multi-platform bundle that leverages the existing installed user base and shared user relationships, envelopers are able to foreclose access to users by a specialized incumbent and capture large market share. Thus, platform providers serving different markets can outcompete providers that serve a single market to the point of driving them out of the market⁹.

When considering competition between the multi-market platform and the single-market platform, envelopment has a strong anti-competitive effect in that it often drives out the smaller competitor by creating and leveraging economies of scale and scope through the leveraging of the shared user base (across the multiple services). However, as advanced during the DMC Forum’s discussion, whether envelopment leads to harmful effects for users is a different and open question. In most cases, envelopment can lead to greater efficiencies and benefit consumers in terms of greater technological integration, greater variety and enhanced consumption experience. In the context of forays in traditional contexts (e.g., automotive, healthcare etc...), envelopment can stimulate innovation and lead to significant technological shifts, whose benefits can permeate across the entire sector. In other cases, when envelopment targets the competitive domain of large platforms, it might also lead to greater competition across platforms as in the case of Google Android creating greater platform competition (*for* the market) with Apple iOS, or Apple Maps and Apple iBook creating competition in markets formerly dominated by single platforms; respectively, Google Maps and Amazon eBook¹⁰.

If consumer welfare is the guiding reference for competition policy, the harmful effects of platform envelopment remain ambiguous; the basis for justifying ex-ante regulatory restrictions on a platform market’s scope might thus be wobbly. There might be other reasons why regulatory intervention might be needed – e.g., when envelopment might preclude superior technologies to emerge in a

⁸ Platform envelopment refers to the practice of taking a set of technological features addressing user needs in a market the platform firm would like to enter and bundle it with the existing features of the existing core platform of the firm.

⁹ Examples of envelopment range from old forays of Microsoft into web browsing (Explorer vs. Netscape) and music streaming (Windows media player vs. RealPlayer) to more recent moves from platform firms such as Google’s entry into productivity software (Google Docs), web browsing software (Chrome), mobile phones operating system (Android), or Apple’s moves into maps application (Maps), music and video streaming (Apple Music and Apple TV+).

¹⁰ With digitalization of the economy increasingly blurring the boundaries of markets, envelopment can lead large platforms to enter into each other “turf” and compete in a broader, contested domain, what Visnjic and Cennamo (2013) call “supra-platform market”.

market or when envelopment may create structural conditions that render the market hardly contestable and stifle future innovation opportunities. If the intention is to establish certainty of the regulatory environment by setting *ex-ante* restrictions, a clear framework demarcating “black” spaces (cases where the risks from platform envelopment are larger than the expected user benefits) from “white” spaces (areas where platform envelopment might be desirable to stimulate innovation) would be needed.

3. Data Size: When do Data lead to Network Effects?

The role that data play for network effects and for reinforcing a dominant position in and over the market(s) of a platform player is another major topic heavily debated. Three aspects must be considered in assessing *when* data are subject to network effects dynamics:

1. Does data-enabled learning occur *within* or *across* users?
2. Is data-enabled learning subject to increasing or decreasing returns to scale?
3. Do product or service's benefits to a user from data-enabled learning increase *concurrently* with others using it?

3.1 Conditions for Data Network Effects

The positive feedback of more users generating more data, which then lead to enhanced learning and thus better products might look like the classical reinforcing feedback typical of network effects – would this be the case, platforms can outcompete rivals by leveraging big data (Gregory et al. 2020). However, **more data from more product usage is not the same as network effects**. In many cases, this feedback reflects the well-known phenomenon of *learning-by-doing*, which might be related to economies of scale (the product gets better as firms learn more by doing as production increases) and scope (firms learn more from producing multiple related products). Yet, the economies of scale or scope linked to learning by doing, and the possible related positive feedback, are different than the network effects¹¹.

For data to lead to network effects, **users will have to enjoy increasing benefits from sharing data** with other users of the same product (direct network effects) or with users on the other side of the platform (indirect network effects) such that coordination across users and products in the platform will be enhanced (Cennamo and Constantinides 2020). These can be specific contexts rather than the “norm” in digital multisided platforms (e.g., Hagiu and Wright 2020a,b; Tucker 2019).

Hagiu and Wright's (2020a) model specifies two conditions that must be met for data-enabled learning to create network effects: learning from one customer should not just translate into a better product or experience for that customer, but also for other customers. Additionally, this product/customer experience enhancement from learning should happen fast enough to affect the current value of the product, i.e., benefit its current users. Only in such cases customers will care about how many other people are adopting the product, hence data will exhibit dynamics similar to those of network effects (Hagiu and Wright 2020a)¹².

¹¹ As put explicitly by Tucker (2019: 686), “economies of scale and scope ... operate through cost savings as production increases, ... network effects ... operate through user benefits enhancement as production increases. Network effects are therefore a reflection of consumers' perception of value, while economies of scale are a reflection of cost-side savings.” In other words, for network effects to exist, value to users of the product should increase with the increasing adoption or use of the product by others (whether those are other similar users or different group of users – e.g., service providers).

¹² Consider the case of Google Nest. What matters is that the focal user uses the product more so that the Nest can learn about the user's personal preferences and offer more value to the user. The customized rather than the standardized use of the product is what delivers most of its consumption benefits to the user. Thus, the user will typically not care about how many other customers Nest has, and thus does not internalize that dimension in her/his consumption choice. As a

For network effects to emerge from data, **the product must improve for all users the more users use the product**. This is a necessary but not sufficient condition for data-driven network effects. Unless the product improves during the consumption lifetime, and the user anticipates this effect – i.e., that the product will improve the more other users will adopt the product – there are no network effects linked to data. Thus, according to the theory advanced in Hagiu and Wright (2020a), the second condition for network effects to emerge from data is that **the product improves over the consumption lifetime with more users adopting it**¹³.

In some cases, particularly when users provide information but also “consume” information provided by other users through the platform and its services (such as might be for e.g. Google Search or TripAdvisor), both conditions might be met, and data network effects can emerge - the more users provide data the higher the value for other users during the consumption lifetime, due to increased accuracy and information updatability (Alaimo and Kallinikos 2017; Alaimo, Kallinikos, & Valderrama 2020). In fact, in such cases, a **market for information** can instantiate through the platform, whereby users are interested in *sizeable and relevant information*; i.e., large data providing reliable information that is of relevance to the user’s needs, interests and preferences (Cennamo 2019).

Consider the case of *Google Search*. There is learning happening *across users* – as more users use the algorithm, it gets better and more reliable; eventually, after a certain threshold, there is but marginal benefits from additional data. However, there is also to some extent *within-user learning*, provided Google Search gets better and generates more benefits for the user the more s/he uses it. When combining across and within user learning, Google Search can generate data-driven network effects. This might explain, for instance, why, despite the very small to zero switching costs to other search engines such as Microsoft’s Bing, users tend to choose and stick to Google Search – because one wants to use more the same search engine so that it learns about herself and improves, but also wants to use the search engine that gives the best results, the user might then care of how many other users are on the same search engine. Once the user realizes that, a coordination problem in adoption might arise and thus, network effects from data access and use might emerge.

To sum up, for network effects to emerge from data, there must be data-enabled learning within- and across-user that benefits concurrently the user during the consumption lifetime.

When data-enabled learning happens only across users or within user, in the majority of cases, data do not lead to network effects dynamics. Nonetheless, data-enabled learning will create switching costs due to the enhanced benefits for the consumer to stick with the product (although this is

result, there is data-enabled learning from product consumption, but no network effects. This is an example of what Hagiu and Wright (2020a) refer to as “within-user learning”, in which the product benefits (functionalities and value) for the user improves with more usage by the focal user.

¹³ In the case of digital maps and navigation systems, an adoption coordination problem might be in place if the product updates and delivers additional information and services concurrently with more product usage by users, such as, for instance, in the case of Google Maps providing current traffic information on roads. In such a case, the focal user might care about how many other users are using concurrently the service as the benefits from the service will depend directly from how many other users are on the same map system network.

unrelated to network effects). To the extent that a sizeable amount of data is required for other products to become competitive alternative offerings in the market, data accumulation might be anticompetitive if there are no alternative means to obtain these data or if it is very costly to do so. On this point, the debate is open between those arguing that digital leads to data-driven dominance effects (Gregory et al. 2020) and those arguing that digital lowers barriers to entry and switching costs (compared to physical products) (e.g., Tucker 2019).

3.2 Exponential Growth vs. Thresholds in Data Scale

The amount of data that is required to activate the learning (about users) sufficient to create a competitive offering in the market is an important element to consider in the analysis of the anticompetitive role of data. Assessing this dimension is perhaps more important than establishing whether or when data-driven network effects exist. Even in the case in which data-driven network effects are in place, if the data threshold required to activate those network effects is small enough to allow entry by other firms, the anticompetitive effects of data might be marginal and will not preclude entry. The key point in the analysis is thus understanding whether data-enabled learning is subject to exponential growth or linked to some data thresholds.

The existing evidence points to possibly some data threshold past which adding more data does not lead to more learning (Amatriain and Basilico 2015; Tucker 2019). In a study about search engine accuracy (as measured by whether a consumer felt the need to repeat the search), Chiou and Tucker (2017) found that more data on what consumers did in the past might not help to improve the search engine due to possibly a “long tail” effect: rather than standardized, many search queries are actually unique. Therefore, what matters is the predictive ability of the algorithm for the specific query of the user. This is akin to a “within user” learning by doing. In another study using Amazon data, authors find no gains in terms of improved forecasting from more data from multiple products (Bajari et al. 2018). Rather than more data, data-enabled learning may proceed from the firm’s ability to use “relevant” data and the “right” algorithm on those data (Bessen et al. 2020; Iansiti and Lakhani 2020; Tucker 2019; Kallinikos and Constantiou 2015). Evidence from these studies suggests that the connection between data and network effects is subject to specific strategic actions and the AI capability of the platform firm (Iansiti and Lakhani 2020), not the other way around. A relevant question for anticompetitive considerations is whether differences in these analytical capabilities can persist or be amplified in favour of the platform firm because of data-enabled learning (Cennamo and Constantinides 2020).

What the minimum threshold of data is in a context and to what extent it creates entry barriers is an empirical question that must be evaluated on a case-by-case basis. More generally, these open issues relate to the other aspect to be considered when assessing the role of data: which data are valuable, when, and to whom.

3.3 Data Network Effects: Policy Considerations

The bottom line of the preceding discussion of data-learning vs. data network effects is that, in most cases, data lead to traditional learning-by-doing rather than network effects, and instrumental to

enable the production of and enhancement of products in a way that benefits users. As a result, users can adopt or continue to use the product due to those benefits and be less likely to switch to alternative products; yet, increase in user switching costs due to those benefits should not be mistaken for lock-in due to network effects. Data, thus, are not anticompetitive in and by themselves. How data are used though might generate market distortions and unfair competition. Accordingly, a number of remedies have been proposed to curtail possible abuse of “data power” including forbidding practices of self-preferencing, mandating data sharing and transparency of algorithms.

3.3.1 Self-preferencing

There is consensus that data practices by platforms such as scooping data from complementors’ and users’ transactions to favor their own services (the issue of “self-preferencing”)¹⁴, or those of preferred partners (the issue of “default option bias” of users) might create the conditions for unfair competition in the platform market with no incremental benefits for the end-user

The fact that platforms are not just an arbiter among complementors but also compete directly with complementors is not an issue per se; in fact, it might stimulate competition, innovation and be value-enhancing overall (see e.g., Hagiú et al. 2020), particularly at early stages of the platform and when a product’s value has strong decay effects and continued innovation is important (Cennamo 2018). Platforms can leverage the data to learn about product niches that are more popular and where complementors’ attention is, and enter with their own products and services to re-direct innovation effort of complementors towards other, less-developed niches in an attempt to rise the overall value for users (Wen and Zhu 2020; Zhu and Liu 2018). Data can thus be used to coordinate innovation effort and shape interactions in the platforms to enhance value creation – self-preferencing’s welfare implications in such cases are not foregone¹⁵.

However, increasing anecdotal evidence indicates that platforms could use data about complementors or tweak the recommendation systems¹⁶ to favor their own services *against* those of competing complementors or to exclude access to the market to services of competing platforms. In those cases, there is consensus that these are competitive unfair practices that would not create any additional value for end users or the overall network; to the contrary, it will damage the focal complementor and its services. Regulatory interventions that target these specific practices might correct these distortions and limit the possibility of platforms to abuse their market orchestration power for pure self-serving interests – see Hagiú, Teh and Wright (2020) for a discussion of the possible policy interventions to address the harm from product imitation and self-preferencing.

¹⁴ Some have documented for instance how Amazon can use data from independent sellers using its own marketplace (such as sales information, how much the vendor paid Amazon for marketing and shipping, and how much Amazon made on each sale) to launch competing products – see Mattioli: <https://www.wsj.com/articles/amazon-scooped-up-data-from-its-own-sellers-to-launch-competing-products-11587650015>.

¹⁵ Using data from Amazon to study Amazon’s entry pattern into third-party sellers’ product spaces, Zhu and Liu (2018) find that Amazon is more likely to target successful product spaces but less likely to enter product spaces that require greater seller efforts to grow. This suggests that Amazon might use data about product transactions to enter spaces with higher value-capture potential. While this practice might create competitive distortions and be unfair and discourage affected third-party sellers, the authors also find that Amazon’s entry increases product demand and reduces shipping costs for consumers. The overall welfare effect might thus be ambiguous (see also the analysis by Hagiú et al. 2020).

¹⁶Notoriously, both U.S. authorities and EU antitrust bodies have opened probes against Amazon, accused of scooping up data from third-party sellers and using that information to compete against them – see: <https://www.wsj.com/articles/amazon-to-face-antitrust-charges-from-eu-over-treatment-of-third-party-sellers-11591871818>; <https://www.ft.com/content/a8c78888-bc0f-11e8-8274-55b72926558f>

3.3.2 Data sharing

Data sharing, a remedy which is being increasingly proposed to lower lock-in effects for users and enable switching to competing networks, is another area of controversy. There are two views here. Embracing the view of platform as utilities, one can conceive of the data generated on the platform as a common, non-rival good (Jones and Tonetti 2020), an “essential facility” or “bottleneck” asset that is needed for companies at large to operate in digital markets. Accordingly, excluding access to such asset would be anticompetitive.

Taking the view of platform as market designer and regulator, data can be conceived qua governance mechanism (Cennamo and Costantinides 2020); i.e., as augmented information instrumental to coordinate the participation and activity of agents on the platform. In this sense, the allocation of access rights to data to one group of users or others would not be neutral on the volume, type and quality of complements and content being produced and exchanged (see Claussen et al. 2013 for an analysis on Facebook’s access to user). Data structure (who generates what type of data and who gets access to what type of data) can critically impact participation into the platform, the type of interactions and the quality and volume of exchanges in a similar fashion of the effect that price structure has. This is one important aspect to consider: when data access restrictions are part of the platform’s policy to enhance coordination across users and innovation effort of complementors, would a regulation imposing shared data as the standardized policy across platforms increase welfare and competition across platforms?

A related issue to consider when treating data as a common good is the well-known problem of commons – opportunistic behavior. In principle, treating data as a non-rival good that must be shared with any company can improve competition *for* the market among big dominant platforms and smaller potential new entrants (Hagiu and Wright 2020). However, in a theoretical model, Hagiu and Wright (2020) show the possible downside of it: if entrants anticipate the data-sharing policy, there’s a moral hazard issue and none would be interested in the first place to invest in data that would be obtained for “free”. When this is the case and when instead platforms will still have an interest to invest in the generation of data under the data-sharing policy is an empirical question. One condition might be related to the economies of scope to be had from data; that is, the extent of value options that data might engender for different and differentiated business applications, which can allow companies to escape a zero-sum game competition context.

There is initial evidence that also complementors can leverage access to user data to manipulate a product’s ranking to gain a competitive edge over rivals’ products¹⁷. We must weigh the risks of possible opportunistic data exploitation by complementors such as this (that would distort intra platform competition) against the potential pro-competitive effect of granting complementors access to user and platform data. This “data freeriding” problem might be bigger – not only it might apply to a larger number of firms and thus have greater competitive distortions in the market; it is also a practice harder to detect and more likely to occur given that the individual complementor will not

¹⁷ Several apps providers in the Apple’s App Store are suspected of manipulating their apps’ rankings by nudging users to give a higher rating <https://www.ft.com/content/bb03ba1c-add3-4440-9bf2-2a65566aef4a?shareType=nongift>. Similarly, a FT investigation found evidence some users have posted thousands of five-star ratings on Amazon in exchange of free products from sellers, which they have then resold on eBay; a practice that violates also Amazon’s own rules - <https://www.ft.com/content/bb03ba1c-add3-4440-9bf2-2a65566aef4a?shareType=nongift>

incorporate in its decisions the negative externalities of its behavior on other agents and on the overall platform marketplace.

3.3.3 Mandating Transparency

Market distortions can also emerge from the way a search and recommendation algorithm direct the focal attention of the user to one or another product. This is a grey area that deserves scrutiny. Hotel recommendations in platforms such as Expedia or Booking are influenced by user reviews, but also by other parameters, including the commissions paid by the specific hotel and other specific deals the hotel might have with the platform, which are not known to the user¹⁸. However, the ranking of recommendations is not neutral to the choice of the consumer as shown in a recent report of the Digital Single Market of the EU Commission – it was found that the top 5 results in a search attract 88% of clicks¹⁹.

One remedy being proposed is mandating transparency on the factors upon which that recommendation is based²⁰. Transparency here means that the platform should reveal the extent of the possible bias to consumers of its recommendation system. This should guarantee that the user can freely take her/his choice about whether or not to follow the “advice” of the algorithm and correct for the possible “default option bias”²¹ (i.e., choosing the default option or the one being recommended). One potential issue with this proposal is that transparency might do little to reduce consumers’ bias; consumers might still find it convenient to default to the options recommended by the platform’s algorithm.

Against this backdrop, allowing independent oversight by third parties can be a preferable solution. There have been some proposals of having platforms providing open APIs that allow approved third parties to audit how the recommendations are done²². A positive aspect of this mechanism is that it would not force platforms to disclose their algorithms, hence, it would protect the value of their innovation. At the same time, it will allow oversight over the system, which can act also as deterrent of the potential abuse of orchestration power by the platform. The possibility of running this kind of tests and audit the platform on the extent the algorithm truly recommends the best product on the basis of the dimensions being claimed officially, might be a plausible solution that balance all the interests at stake.

¹⁸ Recently, Booking.com has introduced a notice that appears on top of the search done in the EU warning the user that an accommodation’s ranking might be affected by “commission paid and other benefits”

¹⁹ https://ec.europa.eu/commission/presscorner/detail/en/IP_20_1301

²⁰ This has been the general direction taken recently, in 2018, by the European Commission, which issues new rules and guidelines to set new standards for online platforms on transparency and fairness.

https://ec.europa.eu/commission/presscorner/detail/en/IP_18_3372

²¹ Forbes has recently reported that, in the case of Amazon ecommerce done through voice assistant Alexa, about 85% of Amazon customers select the recommended Amazon product.

<https://www.forbes.com/sites/kirimasters/2018/06/30/amazon-voice-commerce-a-huge-opportunity-for-brands-or-too-early-to-tell/>

²² See e.g., [https://www.europarl.europa.eu/RegData/etudes/STUD/2019/624262/EPRS_STU\(2019\)624262_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/STUD/2019/624262/EPRS_STU(2019)624262_EN.pdf)

References

- Alaimo C., and Kallinikos J. 2017. Computing the everyday: Social media as data platforms. *The Information Society*, vol. 33: 175-191.
- Alaimo, C., Kallinikos, J., & Valderrama, E. (2020). Platforms as service ecosystems: Lessons from social media. *Journal of Information Technology*, 35(1), 25-48.
- Akman, Pinar (2012). *The Concept of Abuse in EU Competition Law: Law and*. Oxford: Hart Publishing
- Amatriain, X. and Basilico, J., 2015. Recommender systems in industry: A netflix case study. In Ricci, F., Rokach, L., and Shapira, B. (eds.) *Recommender systems handbook* (pp. 385-419). Springer, Boston, MA.
- Anderson EG Jr, Parker GG, Tan B (2014) Platform performance investment in the presence of network externalities. *Information Systems Research* 25(1):152–172.
- Bajari, P., Chernozhukov, V., Hortaçsu, A., & Suzuki, J. (2018). The impact of big data on firm performance: An empirical investigation. NBER Working Paper No. 24334.
- Bessen, J. E., Impink, S., Reichensperger, L., and Seamans, R. (2020) GDPR and the Importance of Data to AI Startups. Available at SSRN: <https://ssrn.com/abstract=3576714>
- Boudreau K., Jeppesen, L. 2015. Unpaid crowd complementors: The platform network effect mirage. *Strategic Management Journal*, vol. 36: 1761-1777.
- Bresnahan T, Orsini J, Yin P-L. 2014. Platform choice by mobile apps developers, mimeo, Stanford University.
- Calvano, E. and M. Polo (forthcoming). Market power, competition and innovation in digital markets: A survey. *Information Economics and Policy*.
- Casadesus-Masanell R., and Hałaburda H. 2014. When Does a Platform Create Value by Limiting Choice? *Journal of Economics and Management Strategy*, 23: 259-293.
- Cennamo C. 2018. Building the value of next-generation platforms: the paradox of diminishing returns. *Journal of Management* 44(8): 3038–3069.
- Cennamo C, Ozalp H, Kretschmer T. 2018. Platform architecture and quality tradeoffs of multihoming complements. *Information Systems Research* 29(2):461–478.
- Cennamo C. 2019. Competing in digital markets: A platform-based perspective. *Academy of Management Perspectives*. <https://doi.org/10.5465/amp.2016.0048>. Available at SSRN: <https://ssrn.com/abstract=3410982>
- Cennamo C., Constantinides P. 2020. On the relationship between data and network effects for user value. Working paper.
- Chiou, L., & Tucker, C. (2017). Search engines and data retention: Implications for privacy and antitrust. National Bureau of Economic Research Working Paper: 23815.
- Claussen J, Kretschmer T, Mayrhofer P. 2013. The effects of rewarding user engagement: The case of Facebook apps. *Information Systems Research* 24(1):186-200.

Constantinides P., Henfridsson O., Parker G.G. 2018. Introduction—Platforms and Infrastructures in the Digital Age. *Information Systems Research* 29(2): 381-400.

Corts KS, Lederman M. 2009. Software exclusivity and the scope of indirect network effects in the U.S. home video game market. *International Journal of Industrial Organization* 27: 121–136.

Cremer J., de MontjoYe Y. & Schwitzer H. (2019), *Competition Policy for the Digital Era*, DG Competition. Report for the European Commission.

De Corniere A., Taylor G. 2020. A model of biased intermediation. *RAND Journal of Economics*, vol. 50: 854-882.

Eisenmann T, Parker G, Van Alstyne, M. 2011. Platform envelopment. *Strategic Management Journal* 32(12): 1270-1285.

Eisenmann TR, Parker G, Alstyne M. 2006. Strategies for two-sided markets. *Harvard Business Review* 84(10): 92–101.

EU Commission (2009). Communication from the Commission - Guidance on the Commission's enforcement priorities in applying Article 82 of the EC Treaty to abusive exclusionary conduct by dominant undertakings (2009/C 45/02). <https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A52009XC0224%2801%29>

EU Commission (2020a). Communication from the Commission - A European Strategy for Data COM(2020) 66 final. <https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1593073685620&uri=CELEX%3A52020DC0066>

EU Commission (2020b). Inception Impact Assessment - Digital Services Act Package. <https://ec.europa.eu/info/law/better-regulation/have-your-say/initiatives/12418-Digital-Services-Act-package-ex-ante-regulatory-instrument-of-very-large-online-platforms-acting-as-gatekeepers>

Evans DS. 2003. Some empirical aspects of multi-sided platform industries. *Review of Network Economics* 2: 191–209.

Furman J., Coyle D., Fletcher A., Marsden P. McAuley D., *Unlocking Digital Competition*, Report of the Digital Competition Expert Panel, UK Treasury.

Gregory R.W., Henfridsson O., Kaganer E., and Kyriakou H. 2020. The role of artificial intelligence and data network effects for creating user value. *Academy of Management Review*, forthcoming.

Hagiu A., and Wright J. 2020a. Data-enabled learning, network effects and competitive advantage. Working Paper, Boston University.

Hagiu, A. and Wright, J., 2020b. When data creates competitive advantage. *Harvard Business Review*, 98(1), pp.94-101.

Hagiu A. 2005. Pricing and commitment by two-sided platforms. *RAND Journal of Economics* 37: 720–737.

Hagiu, A. and J. Wright 2015. Multi-sided platforms. *International Journal of Industrial Organization* 43, 162-174.

- Hagiu A., Tehz T-H., Wright J. 2020. *Should platforms be allowed to sell on their own marketplaces?* Working paper.
- Halaburda H., Oberholzer-Gee F. 2014. The limits of scale. *Harvard Business Review* (April): 1-7.
- Halaburda H., Piskorski M. J., Yildirim P. 2017. Competing by restricting choice: The case of matching platforms. *Management Science*, vol. 64. <https://doi.org/10.1287/mnsc.2017.2797>
- Iansiti, M. and Lakhani, K.R., 2020. *Competing in the Age of AI*. Harvard University Press.
- Jacobides, M.G., Cennamo, C., Gawer, A. 2018. Towards a Theory of Ecosystems. *Strategic Management Journal* 39: 2255–2276.
- Jones C., Tonetti C. 2020. Nonrivalry and the economics of data. *American Economic Review*, 110 (9): 2819-58.
- Kallinikos, J., and I. D. Constantiou. 2015. Big data revisited: A rejoinder. *Journal of Information Technology* 30 (1):70–74.
- Khan, Lina (2017). Amazon's Antitrust Paradox. *Yale Law Journal*, Vol. 126, 712-805.
- Landsman V. and Stremersch S. 2011. Multihoming in two-sided markets: An empirical inquiry in the video game console industry. *Journal of Marketing*, vol. 75: 39-54.
- Lee E, Lee J, Lee J. 2006. Reconsideration of the winner-take-all hypothesis: complex networks and local bias. *Management Science* 52(12): 1838–1848.
- Lee, Robin S. 2013. "Vertical Integration and Exclusivity in Platform and Two-Sided Markets." *American Economic Review*, 103 (7): 2960-3000.
- Morlok, T., Constantiou, I., and T. Hess, 2018. Gone for Better or for Worse? Exploring the dual nature of Ephemerality on social media platforms. In *Proceedings of the 26th European Conference on Information Systems (ECIS)*. Association for Information Systems. AIS Electronic Library (AISeL)
- Ozalp H., Cennamo C., Gawer A. 2018. "Disruption in platform-based ecosystems?", *Journal of Management Studies*, 55: 1203–1241.
- Panico C., and Cennamo C. 2020. User preferences and strategic interactions in platform ecosystems. *Strategic Management Journal*, <https://doi.org/10.1002/smj.3149>.
- Parker, G. G., & Van Alstyne, M. W. 2005. Two-sided network effects: A theory of information product design. *Management Science*, 51: 1494-1504.
- Parker G., Van Alstyne, M. and Jiang X. 2017. Platform ecosystems: How developers invert the firm. *MIS Quarterly*, vol. 41: 255-266.
- Robertson, Viktoria HSE (2020). *Competition Law's Innovation Factor: The Relevant Market in Dynamic Contexts in the EU and the US*. Bloomsbury Publishing
- Rochet JC, Tirole J (2006) Two-sided markets: A progress report. *RAND Journal of Economics*. 37(3):645–667.

Schilling, M. A. 2002. Technology success and failure in winner-take-all markets: The impact of learning orientation, timing, and network externalities. *Academy of Management Journal*, 45: 387-398.

Scott Morton F., Bouvier P. Ezrachi A., Jullien B., Katz R., Kimmelman G. Melamed D. & Morgenstern J., Report of the Committee for the Study of Digital Platforms, Market Structure and Antitrust Committee, Chicago Booth Stigler Center.

Tucker, C., 2019. Digital data, platforms and the usual [antitrust] suspects: Network effects, switching costs, essential facility. *Review of Industrial Organization*, 54(4), pp.683-694.

Van Alstyne M, Parker J, Choudary S (2016) Pipelines, platforms, and the new rules of strategy. *Harvard Business Rev.* (April) 94(4): 54–62.

Venkatraman N, Lee CH. 2004. Preferential linkage and network evolution: a conceptual model and empirical test in the U.S. video game sector. *Academy of Management Journal* 47: 876–892.

Visnjic I, Cennamo C. 2013. The Gang of Four: Acquaintances, Friends or Foes? Towards an Integrated Perspective on Platform Competition. *Academy of Management Annual Meeting Proceedings*, 1362-1367

Zhou Z., Zhang L, and Van Alstyne M. 2020. How users drive platform value. Working paper.

Zhu F, & Iansiti M. 2012. Entry into platform-based markets. *Strategic Management Journal* 33(1): 88-106.

Zhu, F. and Q. Liu (2018). Competing with complementors: An empirical look at amazon.com. *Strategic Management Journal* 39 (10), 2618-2642.