May 20th, 2021

COMPETITION FORUM
LAW & ECONOMICS

Algorithmic Search and Recommendation Systems: The Brightside, the Darkside, and Regulatory Answers

Oliver BUDZINSKI*

To quote this paper: O. BUDZINSKI, "Algorithmic Search and Recommendation Systems: The Brightside, the Darkside, and Regulatory Answers", *Competition Forum,* 2021, n° 0019, https://competition-forum.com.

1. What Are Algorithmic Search and Recommendation Systems?

When consumers consider buying a good (i.e., a commodity or a service), they need to be willing to pay the price of the good (depending on the marginal utility, they expect to derive from the consumption; *Jevons* 1862, 1871; *Menger* 1871; *Walras* 1974). However, additional costs occur during the actual transaction (*Coase* 1937). Such transaction costs consist of all costs that are attached to initiating and concluding the transaction. Part of the initiation process are search and decision costs. Search costs cover all costs related to the collection of relevant information about the good such as time to find information or cognitive capacities spent on searching. Usually, consumers do not attempt to collect every available information. Instead, they stop the searching process when they think they acquired sufficient information to make an informed decision. How much cost consumers are willing to bear depends on individual preferences but also on the importance of the transaction for the individual consumer: routine shopping (e.g., daily products) will usually be associated with a low willingness to bear high transaction costs, whereas in the case of non-routine shopping (e.g., a new car, an expensive holiday trip, a house, etc.), consumers often are willing to invest considerable higher efforts to find information (*Vanberg* 1994; *Vanberg* 2002; *Budzinski* 2003). Notwithstanding, decision costs, i.e., the costs of weighing the pros and cons, risks and chances of each offer in order to decide for the one that best fits the consumer's preferences, matter for virtually all purchasing decisions, albeit to a different extent.

Companies enjoy incentives to help consumers' searching and decision process by offering services providing information about

* Prof. Dr. Oliver Budzinski is Professor of Economic Theory (Chair) and Director of the Institute of Economics at Ilmenau University of Technology, Germany. This paper draws on *Budzinski* (2020) and *Budzinski, Gaenssle* & *Lindstädt-Dreusicke* (2021).

existing offers (search services) and helping hands for the decision (recommendation services). Retailers have always done so by presenting different products of one (heterogeneous) good and by providing information by salespersons. While already the way the information is ordered and presented may entail – voluntary or involuntary – recommendation elements (e.g., due to its ranking), explicit recommendations may also be part of a salesperson's job. Retailers provide search and recommendation services with the goal to increase the number and the value of transactions. Matching the consumer's preferences and building up a positive reputation are usually helpful for salespersons as word-of-mouth may attract or deter new consumers and recurrent transactions make consumers come back or not. Salespersons as search and recommendation service providers may or may not be neutral regarding the choice among the competing products due to their inherent interest in making the consumer buy the product that is most profitable for the selling company (see also section 3 on biases). As such, every salesperson faces some conflict of interest when recommending to consumers – sometimes weaker, sometimes stronger. Beyond this, there usually exist specialized services who only provide search and recommendation but do not conclude the transactions themselves. In the analogue world, they often were non-commercial like non-for-profit product testing services.

The digital economy has considerably changed the nature and the economics of search and recommendation services by applying (self-learning) algorithms utilizing personalized consumer data. This personalized data consists of

(i) standard data about consumer identity, i.e., email-addresses, names, IP-addresses, account information, etc.,

(ii) advanced data revealing either (a) stated preferences by the consumer, e.g., comments, ratings and reviews, "likes" and similar automatized statements, "follows" of persons, goods, and companies, etc., or (b) revealed preferences, e.g., tracking consumers actual browsing, searching, and shopping behavior, and

(iii) derived data, i.e., data created by combining (i) and (ii) with each other as well as with data from similar individuals who most closely match the consumer in question in several dimensions.

Depending on the amount and the quality of the data as well as on the analytical competencies, consumption patterns of individual consumers may be derived from the data allowing for more or less accurate estimations of their preferences. In combination with the digital internet technology, this allows for individualizing and personalizing search rankings and recommendations according to the estimated preferences of the individual consumer. This is achieved by training complex algorithms with the available data from the three types categorized above, so that the algorithm automatically produces rankings of search results and recommendations that seek to match the estimated preferences of the consumer. The knowledge that in particular large online services like Google and YouTube (both subsidiaries of Alphabet), Facebook, WhatsApp and Instagram (all subsidiaries of Facebook), Amazon, Apple, Spotify, WeChat, Yandex, and others may accumulate about their consumers will – on average – considerably exceed what salespersons knew about their consumers in the "old" world.[1]

2. The Brightside of Algorithmic Search and Recommendation Systems: Welfare Benefits

Algorithmic search and recommendation systems entail several advantages for consumer welfare:

(1) They reduce search costs, i.e., consumers find more quickly what they are searching for and, due to the preference-oriented ranking of search results, benefit from a better overview on relevant offers (increasing market transparency). This is particularly relevant in online markets since the number of available goods is usually much higher from online retailers/services. First, storage costs are often significantly lower for online stores/services compared to offline competitors, especially if goods can be stored digitally (e.g., in the case of streaming services). Second, the cost of geography decreases in the online world, so that dispersed demand for niche products, which is too dispersed for local stores to store the good, sufficiently accumulates to make selling these goods profitable (the so-called long tail-effect). The high number of items, in turn, aggravates information overload problems by consumers who need an external pre-structuring by search services in order to receive a cognitively manageable range of offers. At the same time, the sheer amount of information is likely to overstrain even experts, whereas algorithms can (better) handle them.

(2) Furthermore, preference-matching recommendations reduce decision

[1] Of course, a specific salesperson may know more about a specific (often returning) consumer than any algorithmic system may ever do. However, looking at the mass of the cases, algorithms are likely to be superior.

costs. The so-called abundance-of-choice problem resulting from the availability of vastly more goods online (compared to offline) increases the relevance of external recommendation in the digital world – and emphasize the superiority of algorithmic recommendations in dealing with the many information. Empirical studies confirm that most consumers choose among the top ranked recommendations and search results and do not look towards the lower ranked offers (*Lorigo* et al. 2006; *Pan* et al. 2007; *Ghose* & *Yang* 2009), i.e., the algorithmic recommendations are effective.

(3) The improved market overview also facilitates one-stop shopping.

(4) The benefits are particularly high for consumers who have a high adversity against search and decision costs and least relevant for consumers who love the search and decision process.

(5) Transferring the insights from *Vanberg* (1994, 2001) to the digital age, consumers can be expected to follow algorithmic recommendations more closely in the case of low-key and routine consumption decisions than in the case of exceptional and outstanding important transactions (see section 1).

The better the fit of the data-based preference estimation is, the higher is the positive welfare effect from these transmission channels. Individualized recommendations are well used by consumers. In the case of the music streaming service Spotify roughly 40 per cent consume recommended content, whereas Netflix estimates that about 75 per cent of its viewing consumption is driven by its algorithmic recommendations (*Bourreau* & *Gaudin* 2018).

Furthermore, employing algorithmic search and recommendation systems is beneficial and profitable for the companies as well (*Budzinski* & *Kuchinke* 2020):

(1) The individualization of search rankings and recommendations leads to an increase in transactions (because consumers find easier and more of what they were looking for) and a longer and more intensive use of the respective service, thus, increasing demand and turnover.

(2) A longer and extended consumption from the company, in turn, increases the amount of personalized data that the company can collect, including learning from the actual choices of the consumers facing the suggestions from the algorithmic search and recommendation system. This data may be profitably used in several ways:

   a. It may further improve the individualized search rankings and the personalized recommendations, fueling a self-reinforcing mechanism.

b. The analyses based upon the data collected from the consumers are valuable for vertical or horizontal integrated services of the company. For instance, employing user data from its streaming services increases the competitiveness of Netflix or Amazon self-productions of audiovisual content because they can better estimate what viewers probably like. A horizontal example would be Facebook using personalized data from WhatsApp in order to optimize their Instagram service. Profitability then originates from improving related goods and increasing their sales or usage.

c. These data analyses are also interesting for third-parties who are willing to pay for it. For instance, Spotify makes money by selling data analyses (the analysis result, not the data itself) upstream to the music industry. Targeted advertising is another example of this profit channel. Here, online services indirectly sell the result of their data analysis to advertisers through placing their ads so that they reach their data-based target group, i.e., the consumers who are according to the data-based estimations most likely to buy the advertised good.

d. Data-based price discrimination refers to cases where a company employs its user data to estimate the willingness-to-pay of individual consumers and adjust its prices accordingly. Reaping consumers' rents by individualized pricing is obviously highly profitable.

(3) Algorithmic search and recommendation services may be used as a promotional tool for other goods offered by the same company. For instance, Google Search may be inclined to rank search results to other Google subsidiaries like Google Shopping, Google Maps, Google Travel, etc. higher than to their competitors. Another example refers to Amazon offering a marketplace and running a shop on this marketplace. Thus, Amazon may benefit from biasing its search and recommendations services towards his own shop. Similarly, Netflix and

AmazonPrime may be incentivized to direct viewers to their own productions instead of to content from their upstream competitors. Profits are then derived from higher sales and uses of the upstream or downstream goods offered by the respective company.

Altogether, the popularity of algorithmic search and recommendation systems both among suppliers and among consumers comes as no surprise, given the manifold advantages it offers. Notwithstanding, there are some downsides as well, which are addressed in the next section.

3. The Darkside of Algorithmic Search and Recommendation Systems: Misleading Consumers and Abusing Market Power

Profit channel (2)d. (databased price discrimination) is at the detriment of consumer welfare since any quantity-enhancing textbook effect is quickly overcompensated by cross-market effects (i.e., the reaped consumer rent is not available for purchases of other goods on other markets anymore) and eroded by the presence of naïve consumers (*Heidhues* & *Köszegi* 2017). The other profit channels (1) and (2) should mostly not affect consumer welfare in any negative way as long as data analyses' results are traded (and not the personalized data itself) and as long as the less annoying character of targeted advertising (compared to untargeted advertising – because one receives advertising for goods that at least match one's own preferences) is not outdone by an increase in the volume of advertising (*Budzinski* & *Kuchinke* 2020). With respect to some specific goods, algorithmic search and recommendation systems may fuel binging phenomena, i.e., harmful over-consumption of goods (*Gaenssle* & *Kunz-Kaltenhäuser* 2020).[2]

Profit channel (3) from section 2, however, raises concerns. If the providers of search and recommendation systems experience incentives to bias the ranking of search results and recommendations, consumer welfare may be jeopardized in favor of company profits. A priori, providing companies should not experience such incentives because maximizing the fit with individual consumer preferences is profitable (see section 2) – and deviating from the best fit ("bias") jeopardizes consumer satisfaction. Nevertheless, biases can be profitable whenever the provider of the search and recommendation system benefits more from consumers choosing a *specific* candidate from the available product options than if they choose an alternative. If for instance the profit margins for an online marketplace service differ among sellers on this marketplace, the marketplace service

[2] Further aspects like consumption filter bubbles or echo chambers, data-related scale effects, and privacy issues are discussed in *Budzinski*, *Gaenssle* and *Lindstädt-Dreusicke* (2021).

experiences incentives to recommend preferably goods from those sellers where the marketplace service provider's profit margin is highest. Similarly, the incentive to rank these items systematically higher in search results, independent of the consumer's preference, is given.

A particularly relevant case in question is nowadays discussed as the "dual role"-phenomenon. It describes the case where the provider of search and recommendation services also offers its own goods that are part of the search and recommendation items (see the examples of Google, Amazon, and Netflix in section 2). In such cases, algorithms providing search results or recommendations may be tweaked so that the own products (or in-house productions) are systematically upgraded and the goods from competitors of these products systematically downgraded.[3] In the Google Shopping case of the European Commission, for instance, a system was detected through which Google allegedly allocated penalty points to particularly close competitors to their own product (here: competing shopping comparison services), so that they tumbled down the rankings shown to consumers (*European Commission* 2017).

Recently, a new literature has emerged that is analyzing the conditions under which incentives to bias algorithmic search and recommendation systems are likely to occur and reduce social welfare. While there is extensive literature on algorithmic search and recommendation systems from an information technology perspective, their treatment within economics has only just begun. Next to more general discussions of the economics behind algorithmic SRS and their role in the digital economy (*Belleflamme* & *Peitz* 2020; *Gaenssle* & *Budzinski* 2021), the question of welfare effects is addressed in a recent series of modeling papers. They model a monopoly retail service (like a marketplace service or a streaming service) that includes an algorithmic SRS and two or more competing upstream providers of goods (content, commodities, or services), one of them being integrated with the retail service, the other one(s) independent (*Drugov* & *Jeon* 2018; *De Cornière* & *Taylor* 2020; *Padilla*, *Perkins* & *Piccolo* 2020). *Hagiu*, *Teh* and *Wright* (2020) add an outside option for the upstream goods' providers, i.e., allowing for direct sales of upstream firms to consumers. *Bourreau* and *Gaudin* (2018) assume non-integrated upstream suppliers. The way they model demand and, consequently, the extent of heterogeneity among consumers in their models considerably differs between the studies. While the models are principally working for different types of retail services, *Bourreau* and Gaudin (2018) focus on

[3] In particular recommendation biases took also place in the pre-digital world, when salespersons biased their recommendations to goods with a particular high profit margin or to goods for whose sales they received extra payments.

streaming services, *Hagiu*, *Teh* and *Wright* (2020) on marketplace services and *Padilla*, *Perkins* and *Piccolo* (2020) on app store services.

In the absence of vertical integration, incentives for biasing SRS results occur if the retail service earns more from selling goods from upstream company A than from upstream company B (bias in favor of the more profitable sales; *De Cornière* & *Taylor* 2020). In doing so, SRS provider faces a trade-off between setting a high subscription fee and a high level of bias because the platform needs to compensate (marginal) subscribers for bias via a lower subscription fee to ensure their participation (*Bourreau* & *Gaudin* 2018). Thus, services offered at the price of zero (like the Google search engine or Amazon's SRS) can afford a higher bias than services with a positive subscription price (like Netflix streaming service). Otherwise, vertical integration causes incentives to bias SRS results in favor of the own goods (self-preferencing; *Drugov* & *Jeon* 2018; *De Cornière* & *Taylor* 2020; *Hagiu*, *Teh* & *Wright* 2020; *Padilla*, *Perkins* & *Piccolo* 2020). This bias is usually profitable for the vertically-integrated company but harmful for consumer and social welfare (*Drugov* & *Jeon* 2018; *Hagiu*, *Teh* & *Wright* 2020; *Padilla*, *Perkins* & *Piccolo* 2020). Only *De Cornière* and *Taylor* (2020) identify a case for non-harmful bias. They distinguish between "conflict" and "congruence" between the payoffs of the integrated company and its consumers:

- "conflict": the most efficient way for the integrated company to increase the utility of its product for the consumer is to reduce its per-unit mark-up, i.e., decrease the price.
- "congruence": the most efficient way for the integrated company to make its offer more attractive is to improve its upstream good so that it offers higher utility, thus increasing the willingness-to-pay by consumers and allowing higher per-unit mark-ups, i.e., utility and price increasing together.

In this scenario, bias is always harmful for consumer surplus under "conflict" because consumers are mismatched more often, and the favored (integrated) company offers lower utility than its (non-integrated) competitor. "Congruence" can be beneficial if the favored (integrated) company's higher utility goods offset the mismatching but also harmful if it is the other way around.

This literature is still limited, inter alia, as to the monopoly assumption as well as with respect to actual consumer behavior, i.e., when and why do consumers actually follow SRS results. Notwithstanding, several insights can be extracted. According to this limited number of theoretical analyses, incentives for algorithmic search and recommendation bias (self-preferencing) increase with the following characteristics:

- higher market power in the market for algorithmic search and recommendation systems.
- higher market power in the retailing market with which the search and recommendation system is integrated (*Bourreau* & *Gaudin* 2018; *De Cornière* & *Taylor* 2020; *Hagiu* et al. 2020).
- higher market shares even below traditional market power thresholds of an integrated provider on the upstream market of the goods/contents that are listed in search rankings and recommendations (*Drugov* & *Jeon* 2018).
- larger insensitivity of consumers to biased recommendations (*Bourreau* & *Gaudin* 2018; *De Cornière* & *Taylor* 2020), i.e., lower bias elasticity of demand, for instance due to higher search costs for consumers wanting to circumvent the biasing search and recommendation service (*Bourreau* & *Gaudin* 2018), but also due to other factors.
- the existence of essential "superstar" or "must-have" content/goods because, again, consumers find it more difficult to avoid the biasing retail service (*Bourreau* & *Gaudin* 2018; *Gaenssle* & *Budzinski* 2021).
- smaller quality or utility differences between the goods/contents from the integrated and the non-integrated upstream providers (*De Cornière* & *Taylor* 2020; *Padilla* et al. 2020) because consumers are likely to find it more difficult to detect bias.
- more saturated or more mature markets (*Padilla* et al. 2020), i.e., when growth dynamics in the primary markets of the biasing services (i.e., the streaming market or the underlying hardware market as in the case of SRS by smartphone app stores) start to slow down.
- more or more likely options to personalize subscription prices (*Bourreau* & *Gaudin* 2018).

The more of these characteristics are given and the higher the extent of that is, the higher is the probability of the occurrence of harmful self-preferencing. Further research is likely to identify more characteristics along these lines. Altogether, welfare-harming biasing of algorithmic search and recommendation rankings plays only a minor role if the service provider is independent or if vertical integration is limited to the retailer level. In these cases, the probability of harmful bias is not zero. However, it then depends on considerable market power, severely limiting alternatives to the dominant search and recommendation service for consumers. In such cases, effective competition erodes the incentives for biases. Things look different, however, if vertical integration extends to upstream levels which provide/sell the goods that get ranked by the search and recommendation service. This represents the problematic case where harmful bias in the form of self-preferencing must be expected to prevail – even below the common thresholds for dominant positions.

Consumers are vulnerable to vertically-integrated search and recommendation service providers because they

(i) are unable to perfectly identify whether the ranking they see perfectly fits their preferences, and

(ii) are unwilling to spend (scarce) cognitive resources and transactions costs on routine consumption (see sections 1 and 2).

This offers limited scope also for non-dominant companies to bias algorithmic search and recommendation results because consumers are not perfectly likely to switch to another provider in the case of bias.[4] When using this scope, the service providers need to trade-off and balance (a) the danger to frustrate consumers by suboptimal search results and recommendations with (b) the chance of increasing profits due to steering consumers towards more profitable goods and choices. Thus, providers of algorithmic search and recommendation services with an interest in upstream or conglomerate businesses enjoy some market power due to their position within a digital ecosystem rather than because of their market share in the market stage "algorithmic search and recommendation services". This has some implications for competition policy and regulation.

4. Enhanced Competition Policy versus Regulation?

Driven by the impression that traditional competition policy tools may not suffice to combat the anticompetitive challenges of the digital age, several jurisdictions are discussing reforms of their competition rules for digital business and have commissioned expert studies on this subject. *Kerber* (2020) provides an interesting comparison of several of these studies. One common feature is skepticism whether the traditional concept of market power – single-firm dominance of a distinct market – is still adequate to tackle powerful firms within digital ecosystems. In such digital ecosystems, it is notorious difficult to delineate single markets since the interrelations between markets and goods are complex. As the preceding section has shown, the interrelation between a retailing service (like a marketplace, a streaming service, or an app store) employing algorithmic search and recommendation services and upstream good and content producers represent a good example: phenomena of *economic dependence* (*Bougette* et al. 2019) become widespread and power

[4] In other words, the existence of competitive alternatives does not sufficiently affect the scope for the integrated supplier to skip biasing search results and recommendations.

across supply chains but also across markets may be *systemic* rather than based on identifiable market shares or hypothetical monopoly tests (*Budzinski*, *Gaenssle* & *Stöhr* 2020). This fuels a discussion whether an enhanced and empowered competition policy or an ex ante regulation are better suited to deal with such phenomena (inter alia, *Budzinski*, *Gaenssle* & *Stöhr* 2020; *Krämer* 2020; *Marsden* & *Podszun* 2020; *Cabral* et al. 2021; *Vezzoso* 2021). Germany, for instance, focuses on enhancing competition policy competences by broadening the market power concept in its competition law to include outstanding relevance across markets within (digital) ecosystems and relative market power, which both go beyond traditional concepts of dominance (*Budzinski*, *Gaenssle* & *Stöhr* 2020). The European Union, on the other hand, proceeds along the avenue of introducing ex ante regulation of online services with the proposed Digital Markets Act and Digital Services Act (inter alia, *Cabral* et al. 2021; *Podszun* et al. 2021).

Interestingly, some of the studies referenced in section 3 also investigate potential policy remedies against harmful search and recommendation biases, in particular self-preferencing. They conclude:

- banning dual role phenomena including break-up/divestiture of the integrated firm decreases social welfare (*Hagiu* et al. 2020), except if price competition is more relevant to a monopoly retail service than quality/utility competition (*De Cornière* & *Taylor* 2020).
- preventing self-preferencing increases consumer welfare (*Hagiu* et al. 2020; *De Cornière* & *Taylor* 2020), except if it softens competition between goods/content providers, e.g., because of a neutrality obligation requiring a randomized order of search and recommendation rankings (*De Cornière* & *Taylor* 2020), thus eroding the procompetitive effect of algorithmic search and recommendation systems.
- preventing the integrated retail service provider from imitating superior products by independent providers (e.g., through using exclusive marketplace or streaming data about this upstream competitor) increases total welfare but decreases consumer welfare because it erodes innovation incentives (*Hagiu* et al. 2020).
- however, banning both self-preferencing and imitation increases consumer and total welfare (*Hagiu* et al. 2020).
- transparency policies improving consumers' knowledge about the bias (but not in the sense of revealing the properties of the algorithm) yield ambiguous results (*De Cornière* & *Taylor* 2020).

Altogether, a combination of

(a) prohibiting self-preferencing in search and recommendation rankings,
(b) banning the withholding of marketplace or streaming business data that relate to the upstream company's own goods that
(c) addresses service providers that are vertically-integrated or of outstanding relevance within a (digital) ecosystem

appears to be the preferred policy response from an economic perspective. This can be achieved by special responsibilities for powerful service providers as they are common in the context of abuse control in competition policy (Art. 102 TFEU). However, it requires an extended and broadened concept of market power that includes systemic market power. Then, an ex ante regulation is probably not required in order to reach the desired effects.

The EU proposal of a Digital Markets Act addresses large online services that are so-called gatekeepers with a significant impact on the common market, a strong intermediation position, and a durable position in the market. Services that are qualified by the European Commission as being such gatekeepers will have to, inter alia, (i) allow upstream business and commercial users to access the data that they generate in their use of the service and (ii) treat goods offered by the gatekeeper itself more favorably in ranking than similar goods offered by third parties through the gatekeeper's service (*European Commission* 2020a).[5] Thus, with respect to algorithmic search and recommendation services, the critical issues are addressed, albeit with a question mark over the identification problem and the question whether (all) the right and relevant services will be classified under the DMA. Another concern relates to the adaptability of such a regulation to the creative and innovative character of anticompetitive strategies, especially in fast-evolving markets like in the digital economy. The proposal of a Digital Services Act further includes an obligation for more transparency about the algorithms used for search and recommendation rankings (*European Commission* 2020b).[6] Based upon the available economic analysis outlined in this contribution, skepticism about the effects of such a regulation are justified. It may just be a paper tiger without doing much harm, however, interventions into the way service providers shape and develop their algorithms beyond a ban on self-preferencing can quickly go at the expense of the beneficial effects of algorithmic search and recommendation services. A tendency toward "neutral" rankings in the sense of non-data-based or randomized rankings would come along with considerable consumer welfare losses.

Oliver BUDZINSKI

[5] See for further obligations *European Commission* (2020a).

[6] See for more details on the proposed regulation *European Commission* (2020b).

LITERATURE

Belleflamme, P. & Peitz, M. (2020), Ratings, Reviews, Recommendations and the Consumption of Cultural Goods, in: R. Towse & T. Navarrete Hernández (Hrsg.), Handbook of Cultural Economics, 3rd Edition, Cheltenham: Elgar, pp. 466-473.

Bougette, P., Budzinski, O. & Marty, F. (2019), Exploitive Abuse and Abuse of Economic Dependence: What Can We Learn from an Industrial Organization Approach? In: Revue d'Economie Politique, Vol. 129 (2), pp. 261-286.

Bourreau, M. & Gaudin, G. (2018), Streaming Platform and Strategic Recommendation Bias, available from https://ssrn.com/abstract=3290617.

Budzinski, O. (2003), Cognitive Rules, Institutions, and Competition, in: Constitutional Political Economy, Vol. 14 (3), pp. 215-235.

Budzinski, O. (2020), Welfare Effects of Algorithmic Search and Recommendation Systems, in: S. J. Solodovkikov et al. (eds.), Mineral Resources Complex: Engineering and Economic Solutions: XVII International Scientific and Practical Conference, dedicated to the 100th Anniversary of BNTU, Minsk: BNTU 2020, pp. 29-39.

Budzinski, O., Gaenssle, S. & Lindstädt-Dreusicke, N. (2021), Data (R)Evolution - The Economics of Algorithmic Search & Recommender Services, in: S. Baumann (Ed.), Handbook of Digital Business Ecosystems, Cheltenham: Elgar, forthcoming.

Budzinski, O., Gaenssle, S. & Stöhr, A. (2020), Outstanding Relevance Across Markets: A New Concept of Market Power? In: Concurrences, Vol. 17 (3), pp. 38-43.

Budzinski, O. & Kuchinke, B. A. (2020), Industrial Organization of Media Markets and Competition Policy, in: M. B. von Rimscha (ed.), Management and Economics of Communication, Berlin: DeGruyter, pp. 21-45.

Cabral, L., Haucap, J., Parker, G., Petropoulos, G., Valletti, T., and Van Alstyne, M . (2021), The EU Digital Markets Act, Publications Office of the European Union, Luxembourg, 2021, ISBN 978-92-76-29788-8, doi:10.2760/139337, JRC122910.

Coase, R. H. (1937), The Nature of the Firm, in: Economica, Vol. 4 (16), pp. 386-405.

De Cornière, A. & Taylor, G. (2020), A Model of Biased Intermediation, in: Rand Journal of Economics, forthcoming.

Drugov, M. & Jeon, D.-S- (2018), Vertical Integration and Algorithm Bias, Mimeo.

European Commission (2017), Case AT.39740 – Google Search (Shopping), Brussels.

European Commission (2020a), Proposal for a REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL on Contestable and Fair Markets in the Digital Sector (Digital Markets Act), COM(2020) 842 final, Brussels.

European Commission (2020b), Proposal for a REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL on a Single Market for Digital Services (Digital Services Act) and amending Directive 2000/31/EC, COM(2020) 825 final, Brussels.

Gaenssle, S. & Budzinski, O. (2021). Stars in Social Media: New Light Through Old Windows?, *Journal of Media Business Studies*, Vol. 18 (2), pp. 79-105.

Gaenssle, S. & Kunz-Kaltenhäuser, P. (2020), What Drives Binge-Watching? – An Economic Theory and Analysis of Impact Factors, Ilmenau Economics Discussion Papers, Vol. 26 (138).

Ghose, A. & Yang, S. (2009), An Empirical Analysis of Search Engine Advertising: Sponsored Search in Electronic Markets, in: Management Science, Vol. 55 (10), pp. 1605-1622.

Hagiu, A., The, T.-H. & Wright, J. (2020), Should Platforms Be Allowed to Sell on their Own Marketplaces? Working Paper.

Heidhues, P. & Köszegi, B. (2017), Naivete-Based Discrimination, in: The Quarterly Journal of Economics, Vol. 132 (2), pp. 1019-1054.

Jevons, W. S. (1862), Brief Account of a General Mathematical Theory of Political Economy, in: Journal of the Royal Statistical Society, Vol. 24 (2), pp. 282-287.

Jevons, W. S. (1871), The Theory of Political Economy, London: Macmillan.

Kerber, W. (2019), Updating Competition Policy for the Digital Economy? An Analysis of Recent Reports in Germany, UK, EU, and Australia, http://dx.doi.org/10.2139/ssrn.3469624.

Krämer, Jan (2020; ed.), Digital Markets and Online Platforms: New Perspectives on Regulation and Competition Law, CERRE, http://dx.doi.org/10.2139/ssrn.3733346.

Lorigo, L., Pan, B., Hembrooke, H., Joachims, T., Granka, L. & Gay, G. (2006), The Influence of Task and Gender on Search and Evaluation Behavior Using Google, in: Information Processing and Management, Vol. 42 (4), pp. 1123-1131.

Marsden, P. and Podszun, R. (2020). *Restoring Balance to Digital Competition – Sensible Rules, Effective Enforcement*. Berlin: Konrad-Adenauer-Stiftung.

Menger, C. (1871), Grundsätze der Volkswirtschaftslehre, Wien: Braumüller.

Padilla, J., Perkins, J. & Piccolo, S. (2020), Self-Preferencing in Markets with Vertically-Integrated Gatekeeper Platforms, CSEF Working Paper 582.

Pan, B., Hembrooke, H., Joachims, T., Lorigo, L., Gay, G. & Granka, L. (2007), In Google We Trust: Users' Decisions on Rank, Position and Relevancy, in: Journal of Computer-Mediated Communication, Vol. 12 (3), pp. 801-823.

Podszun, R., Bongartz, P. & Langenstein, S. (2021), Proposals on How to Improve the Digital Markets Act. Available at SSRN: http://dx.doi.org/10.2139/ssrn.3788571.

Vanberg, V. J. (1994), Rules and Choice in Economics, London: Routledge.

Vanberg, V. (2002), Rational Choice vs. Program-based Behaviour – Alternative Theoretical Approaches and their Relevance for the Study of Institutions, in: Rationality and Society, Vol. 14 (1), pp. 7-53.

Vezzoso, Simonetta (2021), The Dawn of Pro-Competition Data Regulation for Gatekeepers in the EU. Available at SSRN: http://dx.doi.org/10.2139/ssrn.3772724.

Walras, L. (1874), Éléments d'Économie Politique Pure, Lausanne: Corbaz.